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Do Technical Indicators Enhance the Predictability of the Equity Market Risk Premium? Evidence from Korea

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Abstract

Prior empirical studies suggest that technical indicators may contain information useful for predicting the equity market risk premium and may complement forecasting models based on macroeconomic variables. This paper examines the predictive power of technical indicators in conjunction with macroeconomic variables in the Korean market, focusing on whether technical indicators enhance the predictability of the equity market risk premium. Using monthly data from October 2000 to December 2023, this study evaluates the performance of individual variables and groups of macroeconomic variables and/or technical indicators by extracting principal components and estimating predictive regressions. Both in-sample and out-of-sample tests are conducted to assess the economic implications of the principal component predictive regressions. Contrary to findings from the U.S. and China, the results show that technical indicators in Korea exhibit weak predictive power at a monthly frequency when considered in isolation. However, combining technical indicators with macroeconomic variables substantially improves predictability. In-sample regressions based on principal components extracted from the combined information set yield higher explanatory power than models based solely on macroeconomic variables or technical indicators. Out-of-sample results further confirm that incorporating technical indicators into macroeconomic information leads to meaningful gains in forecasting accuracy for the Korean equity market risk premium.

Keywords: equity market risk premium predictability; macroeconomic variables and technical indicators; in-sample predictability; out-of-sample forecasts; the Korean stock market

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1. Introduction

There has been extensive research on predictive variables for forecasting future equity risk premium, which can be broadly classified into technical and fundamental approaches. Technical analysis relies on information embedded in past prices and trading activity to extract signals about future return movements, and is widely adopted by practitioners in the financial market (Menkhoff, 2010). In academic research, however, greater attention has traditionally been devoted to fundamental predictors, including valuation ratios and macroeconomic variables (Breen et al., 1989; Campbell, 1987; Campbell & Shiller, 1988a, 1988b, 1998; Fama & French, 1988, 1989; Fama & Schwert, 1977; Kothari & Shanken, 1997; Nelson, 1976; Pontiff & Schall, 1998; Rozeff, 1984). Early empirical studies often found limited support for technical trading rules, consistent with the weak-form efficient market

hypothesis (Fama, 1970; Fama & Blume, 1966; James, 1968; Jensen & Benington, 1970; Levy, 1967a, 1967b).

More recent studies, however, provide evidence that technical indicators based on simple trading rules, such as moving averages, trading volume, and momentum, may contain useful predictive information for future returns. Following Brock et al. (1992), several studies document the effectiveness of moving-average trading rules and related indicators for stock returns and portfolio returns (Bessembinder & Chan, 1998; Lo et al., 2000; Han et al., 2013). Trading volume has also been shown to convey information about future returns both theoretically and empirically (Campbell et al., 1993; Blume et al., 1994; Lee & Swaminathan, 2000; Gervais et al., 2001; Kaniel et al., 2012). In addition, a large literature documents momentum effects in stock returns over intermediate horizons (Jegadeesh & Titman, 1993; Conrad & Kaul, 1998; Rouwenhorst, 1998; Griffin et al., 2003), as well as time-series momentum in aggregate returns (Moskowitz et al., 2012; Asness et al., 2013; Huang et al., 2020; Gao et al., 2018). More recent studies continue to document the predictive role of technical indicators in international markets. For example, Liu et al. (2025) examine the contribution of technical indicators in stock return prediction in the Chinese market using deep-learning-based methods and show that technical indicators can improve forecasting performance by a small margin for the Chinese market.

Motivated by these findings, recent studies have examined the joint predictive power of macroeconomic variables and technical indicators for equity risk premiums. Neely et al. (2014) show that both groups of predictors provide statistically and economically significant forecasting power for the U.S. equity risk premium and contain complementary information across business cycles. Sun and Glabadanidis (2022) provide similar evidence for the Chinese market and show that technical indicators can enhance the predictive power of macroeconomic variables, particularly at higher data frequencies.

In this study, we investigate the predictive power of technical indicators in forecasting equity risk premium in Korea, comparing their performance to that of macroeconomic variables. Using standard practices to construct technical indicators following Neely et al. (2014), we assess the performance of individual predictors and, in particular, compare the performance of technical indicators and macroeconomic variables as a group by parsimoniously incorporating information from both groups. Specifically, we employ principal component analysis, as applied by Neely et al. (2014), to extract a selected number of principal components out of the whole groups of macroeconomic variables and/or technical indicators. We then conduct in-sample and out-of-sample tests using monthly data spanning from October 2000 to December 2023.

The analysis is conducted at a monthly frequency, which is standard in the equity premium predictability literature. Monthly data provides a natural compromise between capturing time variation in expected returns and avoiding excessive noise associated with higher-frequency data. Moreover, many macroeconomic predictors such as inflation and industrial production are naturally available at the monthly frequency, making monthly observations the most appropriate frequency for combining macroeconomic and technical information. Using a monthly frequency also facilitates direct comparison with previous studies such as Neely et al. (2014) and Sun and Glabadanidis (2022).

This article contributes to the literature on international stock return predictability by examining the Korean market and complementing existing evidence for the U.S. and Chinese markets. The Korean equity market has several distinct characteristics. First, individual investors play a dominant role, accounting for a large share of ownership and trading activity (Park & Kim, 2014). While institutional investors typically follow momentum trading strategies, individual investors tend to exhibit contrarian behavior

(Shefrin & Statman, 1985; Grinblatt & Titman, 1989; Grinblatt et al., 1995; Odean, 1998; Griffin et al., 2003).

When momentum and contrarian traders coexist, return dynamics may become less persistent and adjust more quickly (Atmaz et al., 2024). Unlike the U.S. market, where momentum traders are more prevalent, the Korean market is largely dominated by individual investors with contrarian tendencies (Bae et al., 2011). As a result, shorter-term return dynamics are likely to be more pronounced in Korea than in the U.S.

Second, foreign investors exert a significant influence on the Korean equity market. Foreign ownership accounts for a substantial share of market capitalization, and foreign investors tend to follow short-term momentum strategies, while domestic institutional investors also exhibit momentum trading and individual investors behave more like contrarian traders (Bae et al., 2011). These heterogeneous trading behaviors create complex interactions among investor groups and may influence return dynamics and the predictive power of technical indicators in ways that differ from those observed in the U.S. and China.

Our analysis builds on Chun (2021), who examines the predictive power of macroeconomic variables for the Korean equity market risk premium. That study compares individual macroeconomic predictors with a principal component regression model summarizing information from multiple macroeconomic variables and finds statistically and economically significant predictability. Our study extends this framework by incorporating technical indicators alongside macroeconomic variables.

The main contributions of our study are as follows. First, we find that technical indicators exhibit weak or limited predictive power for future equity risk premium in the Korean stock market at a monthly frequency. Specifically, only four of 14 individual technical indicators show significant predictability at conventional levels in in-sample regressions. Additionally, we observe that technical indicators exhibit predictive power when using the long-run lags of 5 and 6 months, which are notably shorter than the long-run lags of 9 and 12 months typically identified in the U.S. data. This discrepancy may stem from the shorter-term autocorrelations in the Korean stock market prices, as noted above. Second, and more importantly, we show that the capability to predict the Korean market's equity risk premium can be substantially enhanced by incorporating information from technical indicators into macroeconomic variables, despite the weak predictive power of individual technical indicators. The principal component predictive regression model that combines both groups of technical indicators and macroeconomic variables achieves the highest goodness-of-fit measure in in-sample regressions and produces the smallest mean squared forecast errors in out-of-sample regressions. Furthermore, it outperforms all the other predictive regressions, as well as the benchmark historical average in out-of-sample regression results.

The subsample analysis indicates that the contribution of technical indicators may be regime-dependent. Technical indicators become most informative during periods of financial stress such as the global financial crisis, when combining technical indicators and macroeconomic variables substantially improves predictive performance. In other regimes, however, the incremental contribution of technical indicators is limited. The results are also robust to other alternative specifications. Full sample regressions that control for level shifts in average returns or account for persistence in macroeconomic variables continue to indicate that incorporating technical indicators into macroeconomic variables enhances the predictability of the Korean equity market risk premiums.

The remainder of the paper is organized as follows. Section 2 describes the construction of macroeconomic variables and technical indicators. Section 3 presents the in-sample predictive regressions and robustness analyses. Section 4 reports the out-of-sample fore-

casting results and evaluates predictive performance. Section 5 discusses the economic implications of the predictive models and limitations. Section 6 concludes the paper.

2. Data

We collect monthly data spanning from October 2000 to December 2023 from Statistics Korea and the Bank of Korea Economic Statistics System. The equity risk premiums (ERP) is defined as the difference between the log return on the KOSPI and the log return on a risk-free rate proxied by the interest rate on a 91-day CD. Following the previous literature and data availability in Korea, we construct 12 macroeconomic predictors: dividend-price ratio (DP), dividend yield (DY), earnings-price ratio (EP), book-to-market ratio (BM), short-term interest rate (STR), long-term interest rate (LTY), term spread (TMS), default yield spread (DFY), credit spread (CRS), inflation (INFL), industrial production growth rate (IPGR), and stock variance (SV). Detailed variable definitions are provided in Appendix A Table A1.

We construct standard technical indicators following Neely et al. (2014). The first group consists of moving-average (MA) rules that generate buy ($S_{i,t} = 1$) and sell signals ($S_{i,t} = 0$) based on comparisons between short-term and long-term moving averages:

$$S_{i,t} = \begin{cases} 1 \; if \; MA_{s,t} \geq MA_{l,t} \\ 0 \; if \; MA_{s,t} < MA_{l,t} \end{cases}, \tag{1}$$

where $MA_{j,t} = (1/j)\sum_{i=0}^{j-1} P_{t-i}$ for the MA lag length $j = s, l$, with P_t representing the level of a stock market index. We denote the MA indicator as $MA(s,l)$, where s stands for short-term ($s = 1,\ 2,\ 3$) and l stands for long-term ($l = 5,\ 6$). In contrast to Neely et al. (2014), we employ shorter horizons for the long-term moving averages. Preliminary analysis indicates that technical indicators exhibit little predictive power at longer horizons ($l \geq 7$), while several indicators become significant at horizons of five to six months.

As stated in the introduction, the selection of shorter horizons is also motivated by the institutional and behavioral features of the Korean equity market. In particular, the Korean market is characterized by a large presence of individual investors who tend to follow contrarian trading strategies, which are associated with shorter-lived return dynamics and faster expectation adjustments. This market structure suggests that technical signals may operate over shorter horizons than those typically documented for the U.S. market. Also, moving-average rules with horizons between three and six months often outperform longer horizons in Asian stock markets (Ming-Ming & Siok-Hwa, 2006), and momentum effects in value-weighted portfolios are typically observed over horizons of approximately six months (Kang et al., 2025).

The second group consists of momentum indicators defined as

$$S_{i,t} = \begin{cases} 1 \; if \; P_t \geq P_{t-m} \\ 0 \; if \; P_t < P_{t-m} \end{cases}, \tag{2}$$

as the current stock price higher than its past price m months ago indicates a positive momentum with relatively high expected returns. We denote the momentum indicator with m months momentum as $MOM(m)$ for $m = 5,\ 6$.

The third group consists of volume-based indicators constructed using on-balance volume (Granville, 1963):

$$OBV_t = \sum_{k=1}^{t} TVOL_k I_k, \tag{3}$$

where $TVOL_k$ denotes the cumulative trading volume over a period k and I_k is an indicator variable that equals 1 when the closing price at time k is greater than or equal to the previous closing price, and -1 otherwise. Then, the volume-based indicator can be written as

$$S_{i,t} = \begin{cases} 1 \; if \; OMA_{s,t}^{OBV} \geq OMA_{l,t}^{OBV} \\ 0 \; if \; OMA_{s,t}^{OBV} < OMA_{l,t}^{OBV} \end{cases}, \quad (4)$$

where $OMA_{s,t}^{OBV} = (1/j)\sum_{i=0}^{j-1} OBV_{t-i}$ for the MA lag length $j = s, l$. We denote the volume-based indicator as $VOL(s,l)$ with $s = 1,\ 2,\ 3$ and $l = 5,\ 6$.

Tables 1 and 2 report descriptive statistics for the log equity risk premium together with 12 macroeconomic variables and 14 technical indicators over the sample period from October 2000 to December 2023. The average monthly equity risk premium equals 0.337% while the corresponding standard deviation is 5.922%, implying a Sharpe ratio of 0.057. A number of macroeconomic variables display highly persistent autocorrelations, particularly nominal interest rates and the associated term spreads. On average, the technical indicators exceed 0.5, indicating that buy signals occur more frequently than sell signals over the sample. In Table 1, the Augmented Dickey–Fuller (ADF) tests are additionally conducted to examine the stationarity properties of the macroeconomic variables. While the unit root null is rejected for most variables at the 5% significance level, it cannot be rejected for four variables—STR, LTY, DFY, INFL. To address potential concerns regarding persistence and nonstationarity, we re-estimate the predictive regressions using first differences in these variables as a robustness check.

Table 1. Summary Statistics of Macroeconomic Variables, October 2000 to December 2023.

Variable	Mean	Standard Deviation	Min	Max	Autocorrelation	ADF Test Statistic	Sharpe Ratio
ERP (%)	0.337	5.922	−26.774	19.698	0.053	−8.487 ***	0.057
DP	−4.111	0.244	−4.605	−3.555	0.940	−2.982 **	
DY	−4.104	0.245	−4.585	−3.561	0.944	−2.942 **	
EP	1.928	0.322	0.660	2.635	0.901	−3.896 ***	
BM	4.554	0.178	3.980	5.002	0.924	−3.291 **	
STR (ann%)	3.084	1.461	0.630	6.990	0.979	−2.809 *	
LTY (ann%)	3.913	1.611	1.254	7.860	0.980	−2.060	
TMS (ann%)	0.830	0.742	−0.500	2.960	0.946	−3.242 **	
DFY (ann%)	5.150	1.251	2.140	6.453	0.989	−1.687	
CRS (ann%)	0.763	0.527	0.224	4.380	0.952	−3.597 ***	
INFL (%)	0.204	0.362	−0.744	1.189	0.281	−2.766 *	
IPGR (%)	0.268	1.284	−4.267	5.051	−0.262	−14.340 ***	
SV	0.004	0.006	0.000	0.062	0.481	−6.253 ***	

Notes. ERP is the log equity risk premium of the monthly Korean stock market index. ERP, INFL and IPGR are measured in percent, and STR, LTR, TMS, DFS, CRS are measured in annual percent. The Sharpe ratio is the ratio of the monthly average of the log equity risk premium to its monthly standard deviation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2. Summary Statistics of Technical Indicators, October 2000 to December 2023.

Variable	Mean	Standard Deviation	Min	Max	Autocorrelation
MA(1,5)	0.601	0.491	0.000	1.000	0.494
MA(1,6)	0.597	0.491	0.000	1.000	0.540
MA(2,5)	0.590	0.493	0.000	1.000	0.587
MA(2,6)	0.590	0.493	0.000	1.000	0.632
MA(3,5)	0.572	0.496	0.000	1.000	0.569
MA(3,6)	0.594	0.492	0.000	1.000	0.667
MOM(5)	0.594	0.492	0.000	1.000	0.646
MOM(6)	0.579	0.495	0.000	1.000	0.694
VOL(1,5)	0.597	0.491	0.000	1.000	0.391
VOL(1,6)	0.597	0.491	0.000	1.000	0.435

Table 2. *Cont.*

Variable	Mean	Standard Deviation	Min	Max	Autocorrelation
VOL(2,5)	0.601	0.491	0.000	1.000	0.554
VOL(2,6)	0.604	0.490	0.000	1.000	0.603
VOL(3,5)	0.615	0.487	0.000	1.000	0.584
VOL(3,6)	0.601	0.491	0.000	1.000	0.620

Note. Since technical indicators are coded as binary signals (1 or 0), the mean is the share of buy signals and the standard deviation equals $\sqrt{\bar{p}(1-\bar{p})}$. Therefore, different indicator rules may have identical means and standard deviations if they produce the same buy-signal frequency.

The relatively small Sharpe ratio of the ERP indicates limited time-series variation in expected returns, which makes return predictability in the Korean market inherently challenging. In such environments, technical indicators are less likely to exhibit strong predictive power.

3. In-Sample Analysis

3.1. Econometric Methods for In-Sample Analysis

3.1.1. Bivariate Predictive Regressions

In this paper, we explore the predictability of future equity risk premium by adopting the following standard bivariate regression model:

$$r_{t+1} = \alpha_i + \beta_i z_{i,t} + \varepsilon_{i,t+1}, \tag{5}$$

where r_{t+1} denotes the log equity risk premium on the KOSPI from period t to $t+1$; $z_{i,t}$, $i = 1, \cdots, 12$, denotes a macroeconomic predictive variable at time t, and $\varepsilon_{i,t+1}$ is the zero-mean regression error term. The predictive variable $z_{i,t}$ has no predictive power under the null hypothesis, $\beta_i = 0$ in Equation (5), and we test this null hypothesis against a one-sided alternative hypothesis following the recommendation by Inoue and Kilian (2005) to improve the statistical power of in-sample predictability tests. For this purpose, we impose either positive or negative sign on each regressor $z_{i,t}$ to have its slope coefficient β_i positive under the alternative hypothesis and test H_0: $\beta_i = 0$ against H_A: $\beta_i > 0$ using the ordinary least squares (OLS) estimate of β_i in Equation (5).

For technical indicators, we replace $z_{i,t}$ with $S_{i,t}$ from (1), (2), or (4) in the predictive regression model (5) as

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}, \tag{6}$$

where we test H_0: $\beta_i = 0$ against H_A: $\beta_i > 0$. Since $S_{i,t}$ takes a value of either 0 or 1, the regression model (6) tests whether the future equity risk premium under the bullish signal of unity is higher in average than under the bearish signal of zero.

When the predictive variables in Equations (5) and (6) are highly persistent and correlated with past regression error terms—commonly observed in many financial ratio variables—the OLS estimator for β_i may become biased, which inflates the test statistics and results in size distortions that favor predictability. To address this issue, we construct the test statistics using a heteroskedasticity-consistent standard error estimator and apply a wild bootstrap procedure to compute p-values, following the approach of Neely et al. (2014). This method accounts for both the persistence of the predictors and the variance–covariance structure among the variables.[1]

3.1.2. Principal Component-Based Forecasting Regressions

In order to explore and compare the capacity of the entire set of macroeconomic variables and/or technical indicators to forecast the future equity risk premium, we incor-

porate information from multiple predictive variables by extracting principal components to estimate a multivariate predictive regression model. Let $X_t = (X_{1,t}, \cdots, X_{N,t})'$ denote the N-vector of the entire set of macroeconomic variables $(N = 12)$ or technical indicators $(N = 14)$. Following Stock and Watson (2002) and Ludvigson and Ng (2007), we can obtain the K-vector of principal components from the following dynamic factor model:

$$X_t = \lambda' F_t + e_t, \tag{7}$$

where F_t and λ are the K-vectors of principal components and factor-loadings, respectively, and e_t is the N-vector of error terms. Allowing the error terms to be serially correlated and heteroskedastic, Chamberlain and Rothschild (1983) and Bai (2003) propose an approximate factor model to estimate $\widehat{F}_t$ and $\widehat{\lambda}$ in Equation (7). Let $\widehat{F}_t^{ECON} = (\widehat{F_{1,t}}^{ECON}, \ldots, \widehat{F_{K,t}}^{ECON})'$, $\widehat{F}_t^{TECH} = (\widehat{F_{1,t}}^{TECH}, \ldots, \widehat{F_{K,t}}^{TECH})'$, and $\widehat{F}_t^{ALL} = (\widehat{F_{1,t}}^{ALL}, \ldots, \widehat{F_{K,t}}^{ALL})'$ denote the vectors containing the first K principal components extracted from 12 macroeconomic variables, 14 technical indicators, and all 26 variables, respectively. Then the principal component predictive regression can be written as

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \widehat{F}_{k,t}^{i} + \varepsilon_{t+1} \text{ for } i = ECON,\ TECH,\ ALL, \tag{8}$$

where we denote the predictive regression models based on $\widehat{F}_t^{ECON}$, $\widehat{F}_t^{TECH}$, and $\widehat{F}_t^{ALL}$ as the PC-ECON, the PC-TECH, and the PC-ALL models, respectively.

In Equation (8), the principal components can parsimoniously capture the important common fluctuations among a large number of macroeconomic variables and/or technical indicators to deliver relevant information for return prediction. This approach reduces dimensionality and mitigates multicollinearity among highly persistent and correlated predictors while maintaining a parsimonious predictive regression specification. We allow the number of principal components to range from one to three and select the value of K for each group of predictive variables using the adjusted R-squared. We estimate the OLS estimator for β_k in Equation (8) to conduct inference for predictability, and conduct our inferences based on the t-statistics using the heteroskedasticity-consistent standard errors to compare with wild bootstrapped p-values.

Since principal components are estimated from the predictor set, they may contain measurement errors. However, when principal components are extracted from a sufficiently large set of predictors, they provide consistent estimates of the underlying common variation. For this reason, factor-based predictive regressions have been widely used in the return predictability literature (Stock & Watson, 2002; Ludvigson & Ng, 2007; Neely et al., 2014). The measurement errors can be further mitigated by heteroskedasticity-consistent standard errors and wild bootstrap procedures.

3.1.3. Evaluating Predictability During Business Cycle Expansions and Recessions

Recently, researchers often seek to investigate whether forecasting models perform differently during periods of business cycle expansions and recessions. Neely et al. (2014) propose to compute the conventional R^2 statistic using an indicator variable identifying the periods of cyclical expansions and recessions as follows:

$$R_{i,c}^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c \hat{\varepsilon}_{i,t}^2}{\sum_{t=1}^{T} I_t^c (r_t - \bar{r})^2} \text{ for } c = EXP,\ REC, \tag{9}$$

where $R_{i,EXP}^2$ and $R_{i,REC}^2$ denote the R-squared statistics for expansion and recession periods, respectively. I_t^{EXP} (I_t^{REC}) is an indicator variable that takes a value of unity, when month t is an expansion (recession) and zero otherwise, $\hat{\varepsilon}_{i,t}$ is the fitted regression error term of

the full-sample predictive regression models (5), (6) and (8), $\bar{r}$ is the full-sample mean of r_t, and T is the number of full-sample observations. It should be noted that the $R^2_{i,EXP}$ and $R^2_{i,REC}$ statistics can be negative unlike the full-sample R^2 statistic. In this paper, we use the business cycle expansion and recession dates published by Statistics Korea, a government body handling national statistical information.

3.2. In-Sample Regression Results

3.2.1. Full Sample Analysis

Tables 3–5 present the in-sample regression estimates of the slope coefficient β_i, the t-statistics with heteroskedasticity-consistent standard error estimators, and the full-sample R^2 statistics along with the R^2_{EXP} and R^2_{REC} statistics for the bivariate regression models (5) and (6), as well as for the principal component regression model (8). The regressions contain 278 observations after accounting for lagging regressors. In Table 3, the four prominent macroeconomic variables, namely DP, DY, BM and TMS, exhibit significant predictive power at conventional levels in the Korean market. The R^2 statistics in the fourth column are relatively small, all below 3%. As for these goodness-of-fit measure in predictive regressions, even a monthly R^2 as low as 0.5% can still be economically meaningful for mean-variance investors (Campbell & Thompson, 2008). Notable, the R^2 statistics for the four macroeconomic variables in panel A with the significant t-statistics surpass this 0.5% benchmark and the R^2 statistics for BM is 2.66%, which is the largest R^2 among the bivariate predictive regressions. The last two columns present the R^2_{EXP} and R^2_{REC} statistics, which indicate how equity risk premium predictability varies across expansionary and recessionary periods of the business cycle. In the Korean market, equity risk premium predictability is considerably higher during expansions compared to recessions for most macroeconomic variables, including DP, DY, BM and TMS. This contrasts with the findings in the U.S. market, which report that equity risk premium predictability is higher for recession rather than expansions (Neely et al., 2014).

Table 3. In-sample Predictive Regression Results: Bivariate Predictive Regressions with Macroeconomic Variables.

Predictor	Slope Coefficient	*t*-Statistic	R^2 (%)	R^2_{EXP} (%)	R^2_{REC} (%)
DP	3.01	2.18 **	1.54	2.94	−0.37
DY	3.31	2.25 **	1.88	3.57	−0.45
EP	0.50	0.39	0.08	−0.05	0.25
BM	5.43	2.38 **	2.66	3.14	2.00
STR	0.18	0.62	0.21	0.21	0.21
LTY	−0.02	−0.06	0.00	0.03	−0.04
TMS	0.79	1.57 *	0.97	2.13	−0.61
DFY	0.11	0.35	0.06	0.03	0.10
CRS	0.82	0.95	0.54	2.38	−2.00
INFL	1.00	0.91	0.37	−0.42	1.45
IPGR	−0.06	−0.21	0.02	−0.05	0.11
SV	67.16	0.80	0.39	1.34	−0.90

Notes. * and ** indicate significance at the 10% and 5% levels, respectively.

Concerning the technical indicators in Table 4, four of the 14 indicators—MA(2,5), VOL(2,5), VOL(2,6) and VOL(3,5)—demonstrate significant predictive power at the 10% significance level, at least, in the Korean market. These indicators also have the R^2 statistics surpassing the 0.5% benchmark, indicating economically meaningful predictability. Compared to the U.S. market, where most of the technical indicators exhibit strong predictive power with long-run lag lengths of 9 and 12 months, the Korean market presents much weaker predictability for the technical indicators. Fewer than half of the technical indicators

demonstrate significant predictability with long-run lag lengths of 5 and 6 months. The slope coefficient estimates suggest that the average difference in predicted future equity risk premium between buy and sell signals in the Korean market ranges from 11 to 143 basis points. With respect to differences in predictability across different business cycles, all the significant technical indicators exhibit substantially higher predictability during expansions than during recessions.

Table 4. In-sample Predictive Regression Results: Bivariate Predictive Regressions with Technical Indicators.

Predictor	Slope Coefficient	*t*-Statistic	R^2 (%)	R^2_{EXP} (%)	R^2_{REC} (%)
MA(1,5)	0.41	0.53	0.12	0.41	−0.30
MA(1,6)	0.22	0.29	0.03	0.14	−0.11
MA(2,5)	1.02	1.34 *	0.72	2.00	−1.04
MA(2,6)	0.81	1.07	0.46	1.02	−0.32
MA(3,5)	0.93	1.27	0.61	1.33	−0.39
MA(3,6)	0.19	0.26	0.03	0.12	−0.11
MOM(5)	0.90	1.17	0.56	0.12	1.15
MOM(6)	0.11	0.14	0.01	0.02	−0.01
VOL(1,5)	0.33	0.45	0.08	0.42	−0.40
VOL(1,6)	0.65	0.86	0.29	1.03	−0.73
VOL(2,5)	1.27	1.66 *	1.10	2.82	−1.25
VOL(2,6)	1.43	1.86 **	1.40	2.66	−0.33
VOL(3,5)	1.16	1.52 *	0.91	3.17	−2.20
VOL(3,6)	0.28	0.37	0.05	0.30	−0.29

Notes. * and ** indicate significance at the 10% and 5% levels, respectively.

Table 5. In-sample Predictive Regression Results: Principal Component Predictive Regressions.

Predictor	Slope Coefficient	*t*-Statistic	R^2 (%)	R^2_{EXP} (%)	R^2_{REC} (%)
Panel A. Based on Macroeconomic Variables					
$\hat{F}_1^{ECON}$	−0.20	−0.87	2.99	6.15	−1.35
$\hat{F}_2^{ECON}$	0.47	2.09 **			
$\hat{F}_3^{ECON}$	0.47	1.55			
Panel B. Based on Technical Indicators					
$\hat{F}_1^{TECH}$	0.15	1.13	0.53	1.43	−0.70
Panel C. Based on All Variables					
$\hat{F}_1^{ALL}$	0.10	0.76	4.46	8.94	−1.70
$\hat{F}_2^{ALL}$	−0.17	−0.78			
$\hat{F}_3^{ALL}$	0.71	3.10 ***			
$\hat{F}_4^{ALL}$	−0.37	−1.33			

Notes. ** and *** indicate significance at the 5% and 1% levels, respectively.

Turning to the principal component-based forecasting regressions, we classify the predictive variables into three groups: macroeconomic variables, technical indicators, and a combination of both. Panel A of Table 5 presents the estimation results for the PC-ECON model in Equation (8), where principal components are derived from a set of macroeconomic variables with $K = 3$, chosen to maximize the adjusted R^2. The estimated slope coefficient on the second principal component is statistically significant at the 5% level. The fourth column reports the R^2 statistic of 2.99%, which exceeds the 0.5% benchmark and slightly surpasses the largest R^2 statistic obtained from the bivariate predictive regressions. The R^2_{EXP} and R^2_{REC} statistics in the last two columns suggest that return predictability based on the set of macroeconomic variables is stronger in expansionary periods relative to recessionary periods.

Panel B presents the estimation results for the PC-TECH model in Equation (8), which utilizes principal components derived from the technical indicators with $K = 1$ chosen based on the adjusted R^2. The estimated coefficient on the first principal component is not statistically significant at conventional levels, while the R^2 statistic is 0.53%, only marginally above the 0.5% benchmark. Similar to the PC-ECON model, the PC-TECH model reveals stronger return predictability during business-cycle expansions than recessions according to the R^2_{EXP} and R^2_{REC} statistics in the last two columns. However, it does not improve upon the bivariate predictive regression model employing individual technical indicators. Overall, at a monthly frequency, technical indicators in Korea collectively exhibit limited ability to forecast the future equity risk premium.

Nevertheless, combining information from macroeconomic variables with technical indicators substantially enhances the capability to predict the Korean market's equity risk premium. Notably, in the fourth column of Panel E, the R^2 statistic obtained from the PC-ALL model stands at 4.46%, markedly surpassing not only the simple sum of the R^2 statistics of the PC-ECON and the PC-TECH models, but any other in-sample R^2 statistic reported in the fourth column of Table 2. Moreover, Panel E indicates that the slope coefficient estimate for the third principal component in the PC-ALL model is statistically significant at the 1% level. The fifth and sixth columns further highlight the largest disparity between the R^2_{EXP} and R^2_{REC} statistics, suggesting that the PC-ALL model exhibits markedly stronger predictability of the Korean market's equity risk premium during expansions than during recessions.

3.2.2. Robustness to Structural Heterogeneity

To further assess the stability of the predictive relationships documented above, this subsection examines whether the in-sample regressions results are sensitive to structural heterogeneity over time. Specifically, this study conducts subsample regressions and estimate full-sample predictive regressions augmented with regime-specific dummy variables to evaluate whether the predictive relationships remain stable across different market environments.

To this end, the full sample is divided into four economically meaningful subperiods. The first subsample, from October 2000 to December 2006, corresponds to the pre-global financial crisis (GFC) period. The second subsample, from January 2007 to December 2012, covers the GFC and the European sovereign debt crisis. The third subsample, from January 2013 to December 2019, represents the post-crisis period characterized by a prolonged low-volatility market environment in Korea, often referred to as the "BOXPI" phase, during which the KOSPI exhibited relatively stagnant performance compared to major global equity markets (Kim et al., 2022). The fourth subsample, from January 2020 to December 2023, corresponds to the COVID-19 period. In addition to estimating the models separately across subsamples, the study augments the baseline predictive regression in Equation (8) by including dummy variables corresponding to the GFC, BOXPI, and COVID-19 periods, with the pre-GFC period serving as the reference regime. This regression specification allows to control for structural level differences across market regimes.

Table 6 reports the in-sample R^2 statistics across subsample periods. The results indicate that return predictability varies over time. In the pre-GFC and COVID-19 periods, the PC-ECON model exhibits relatively strong explanatory power ($R^2 = 9.21\%$ and 19.39%), while the PC-TECH model shows little predictive ability. As a result, the PC-ALL model delivers explanatory power comparable to that of PC-ECON model ($R^2 = 8.90\%$ and 18.46%). During the GFC period, both macroeconomic variables and technical indicators become informative, and the PC-ALL model achieves the highest explanatory power. In particular, the R^2 of the PC-ALL model (9.26%) substantially exceeds that of the PC-ECON

model (4.90%), indicating that technical indicators provide complementary information during periods of financial stress.

Table 6. In-sample Predictability across different Market Regimes.

Predictive Models	Baseline Regression	Subsample				Full Sample w/Dummies
		Pre-GFC	GFC	BOXPI	COVID	
PC-ECON	2.99	9.21	4.90	0.93	19.39	5.39
PC-TECH	0.53	0.00	3.19	0.00	0.02	1.05
PC-ALL	4.46	8.90	9.26	0.17	18.46	6.45

Notes: The table reports in-sample R^2 (%) from predictive regressions estimated over different subsamples. The subsamples correspond to the pre-GFC (2000.10–2006.12), crisis (2007.01–2012.12), BOXPI (2013.01–2019.12), and COVID-19 (2020.01–2023.12) periods. The last column reports the R^2 (%) of full-sample regressions augmented with regime-specific dummy variables.

In contrast, predictability weakens considerably during the post-crisis BOXPI period, consistent with a prolonged low-volatility environment in which variation in expected returns is limited. Overall, the subsample results reveal that the incremental contribution of technical indicators is most pronounced during highly volatile market conditions, whereas their incremental contribution diminishes in other regimes.

The last column of Table 6 reports the in-sample R^2 statistics from full-sample regressions augmented with regime-specific dummy variables. Controlling for structural level shifts across different market regimes increases explanatory power for all models. Importantly, however, the PC-ALL model continues to outperform the PC-ECON model, with R^2 rising from 5.39% to 6.45%. This finding indicates that even after accounting for structural heterogeneity in average returns, incorporating technical indicators into macroeconomic variables enhances the predictability of the Korean equity market risk premiums. The improvement suggests that the contribution of technical indicators is not driven by regime shifts but reflects additional informational content beyond macroeconomic variables.

3.2.3. Robustness to Persistence and Nonstationarity in Macroeconomic Variables

As several macroeconomic variables documented in Table 1 exhibit high persistence, the study re-estimates the in-sample predictive regressions for the PC-ECON, PC-TECH and PC-ALL models using an alternative specification in which the four variables—STR, LTY, DFY, INFL—that fail to reject the unit-root null at the 5% level are first-differenced. It is important to note that concerns regarding persistence in macroeconomic variables are already addressed in the baseline regression analysis through the use of heteroskedasticity-consistent standard errors and wild bootstrap p-values. The comparison between the baseline and the differenced specifications therefore serves as an additional robustness check.

Table 7 reports the in-sample predictive regression results under the alternative specification. Overall, the results are broadly consistent with the baseline findings. In particular, the PC-ALL model continues to deliver the highest explanatory power, with an R^2 statistic of 4.49%, surpassing that of the PC-ECON model ($R^2 = 4.16\%$). This confirms that the incremental predictive power obtained by combining macroeconomic variables and technical indicators is not driven by persistence in macroeconomic predictors. Moreover, the R^2 statistics under the expansionary or recessionary business cycles yield patterns similar to those in the baseline specification.

Interestingly, the explanatory power increases modestly for both the PC-ECON and PC-ALL models under the alternative specification, suggesting that differencing highly persistent macroeconomic variables may help both models to extract information more efficiently. However, this does not necessarily imply that differencing provides a superior representation of predictive relationships, as it may remove economically meaningful

economic information embedded in long-run dynamics of macroeconomic variables. A more sophisticated econometric model may therefore be desirable to capture both long-run and short-run dynamics, which we leave for future research.

Table 7. In-sample Predictive Regression Results: Baseline and Alternative Regressions.

Predictive Models	R^2 (%)		R^2_{EXP} (%)		R^2_{REC} (%)	
	Baseline	Alternative	Baseline	Alternative	Baseline	Alternative
PC-ECON	2.99	4.16	6.15	8.34	−1.35	−1.59
PC-TECH	0.53	0.50	1.43	1.40	−0.70	−0.73
PC-ALL	4.16	4.49	8.94	8.76	−1.70	−1.39

4. Out-of-Sample Analysis

4.1. Econometric Methods for Out-of-Sample Analysis

Following the in-sample predictability analysis from the previous section, we now conduct out-of-sample predictability tests on 12 macroeconomic variables and 14 technical indicators. Out-of-sample tests offer a more reliable assessment of a model's real-world performance, as they evaluate predictive accuracy on new data not used in the model's parameter estimation. Additionally, these tests help mitigate overfitting issues caused by data mining, highlighted by Clark (2004). Indeed, Welch and Goyal (2008) find that many commonly used predictive variables in the U.S. market have been reported to perform poorly in out-of-sample tests. To ensure robustness of in-sample predictability tests, we extend our analysis to investigate the out-of-sample predictability of 26 macroeconomic variables and technical indicators in the Korean market.

For the out-of-sample tests, we first divide the total sample into two sub-periods: the initial in-sample estimation period and the forecast evaluation period. The initial in-sample estimation period is set to approximately one-third of the total sample, covering October 2000 to October 2008, while the forecast evaluation period spans from November 2008 to December 2023, comprising 182 observations. At each month t, we estimate the OLS estimates of intercept and slope coefficient in the predictive regression models (5) and (6), and generate an out-of-sample forecast for future equity risk premium for the following month,

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} x_{i,t}, \tag{10}$$

where $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are the OLS estimates from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{x_{i,s}\}_{s=1}^{t-1}$. In Equation (10), $x_{i,t} = z_{i,t}$ for the macroeconomic variables and $x_{i,t} = S_{i,t}$ for the technical indicators.

In order to evaluate out-of-sample predictability for principal components regression models, we generate out-of-sample forecasts using the model (8),

$$\hat{r}^i_{t+1} = \hat{\alpha}_t + \sum_{k=1}^{K} \hat{\beta}_{t,k} \hat{F}^i_{1:t,k,t} \text{ for } i = ECON,\ TECH,\ ALL, \tag{11}$$

where $\hat{F}^i_{1:t,k,t}$ is the k-th principal component estimated from the 12 macroeconomic variables and/or the 14 technical indicators using the data up to time t, and $\hat{\alpha}_t$ and $\hat{\beta}_{t,k}$ are the OLS estimates from the regression model (8) based on the observations through time t.

We evaluate the performance of out-of-sample forecasts based on the out-of-sample R^2 statistics (R^2_{OS}) proposed by Campbell and Thompson (2008) and the $MSFE$-adjusted statistics proposed by Clark and West (2007). The R^2_{OS} statistic is given by

$$R^2_{OS} = 1 - \frac{MSFE_{model}}{MSFE_{HA}}, \tag{12}$$

where $MSFE_{model} = \frac{1}{T-R}\sum_{t=R}^{T-1}(r_{t+1} - \hat{r}_{t+1})^2$ and $MSFE_{HA} = \frac{1}{T-R}\sum_{t=R}^{T-1}(r_{t+1} - \bar{r}_{t+1})^2$. This statistic assesses the proportional reduction in $MSFE$ for the given predictive models in Equations (12) and (13) relative to the benchmark historical average forecast, $\bar{r}_{t+1}$. A positive value of R^2_{OS} indicates that the given predictive regression model yields a lower $MSFE$ than the historical average. Similar to their in-sample counterparts, monthly R^2_{OS} values exceeding 0.5% are considered economically significant.

The second out-of-sample statistic, the $MSFE$-adjusted statistic, formally tests the null hypothesis H_0: $R^2_{OS} \leq 0$ against the alternative H_A: $R^2_{OS} > 0$. Under the null hypothesis, the historical average $MSFE$ ($MSFE_{HA}$), is less than or equal to the predictive regression model $MSFE$ ($MSFE_{model}$).

As a benchmark equity risk premium forecast, we use the following historical average forecast:

$$\hat{r}^{HA}_{t+1} = \frac{1}{t}\sum_{s=1}^{t} r_s. \tag{13}$$

This historical average forecast based on the assumption that the expected equity risk premium remain constant over time has been a widely used benchmark in financial research. Studies by Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), Goyal and Welch (2003), and Welch and Goyal (2008) have adopted it, particularly because many commonly used predictive variables have failed to outperform this simple historical average.

4.2. Out-of-Sample Regression Results

Tables 8 and 9 present the out-of-sample regression results for bivariate and principal component predictive regressions based on macroeconomic variables and/or technical indicators. Table 8 focuses on models that employ individual macroeconomic variables. According to the R^2_{OS} statistics reported in the second column, most macroeconomic variables fail to outperform the historical average benchmark. However, the BM and TMS variables stand out with showing positive R^2_{OS} values greater than 0.5% and significantly lower $MSFE$s than the historical average at the 10% level, as shown by the $MSFE$-adjusted statistics in the fourth column. These findings align with Welch and Goyal (2008), who similarly observed poor out-of-sample predictive power for many macroeconomic variables in the U.S. In line with the in-sample regression results reported in Section 3.2.1, more than half of the macroeconomic variables better predict the Korean equity risk premium during expansions than recessions in out-of-sample predictions, as shown by the $R^2_{OS,EXP}$ and $R^2_{OS,REC}$ statistics in the fifth and sixth columns.

Individual technical indicators in Table 9 also reveal weak out-of-sample predictive power as shown by the $MSFE$s. While four of the R^2_{OS} statistics in third column are positive, and three of them exceed 0.5%, only two indicators, VOL(2,6) and VOL(3,5), have $MSFE$s significantly lower than the historical average at conventional significance levels. Unlike the in-sample regression results, only five indicators demonstrate stronger predictive power during expansions than recessions, as shown by the $R^2_{OS,EXP}$ and $R^2_{OS,REC}$ statistics in the fifth and sixth columns. This discrepancy is likely due to the generally weak predictive power of individual technical indicators, as indicated by the negative $R^2_{OS,EXP}$ and $R^2_{OS,REC}$ values.

Second panel of Table 9 presents the out-of-sample forecasting results for principal component-based predictive regressions using macroeconomic variables and/or technical indicators. The PC-ECON model, which captures information from macroeconomic variables, exhibits a positive R^2_{OS} value exceeding 0.5% and an $MSFE$ significantly lower than the historical average at the 10% level. In contrast, the PC-TECH model, which relies solely on technical indicators, fails to demonstrate meaningful out-of-sample predictive power. Its R^2_{OS} statistic in the second column is negative, and its $MSFE$-adjusted statistic in the

third column is statistically insignificant, indicating that technical indicators as a group do not outperform the benchmark historical average forecast in Korea.

Table 8. Out-of-sample Forecasting Results: Historical Average and Macroeconomic Variables.

Predictor	MSFE	R^2_{OS} (%)	MSFE-Adjusted	$R^2_{OS,EXP}$ (%)	$R^2_{OS,REC}$ (%)	$\bar{(\hat{e})}^2$	Rem. Term
HA	23.58					0.04	23.54
DP	24.73	−4.86	0.56	−1.52	−26.03	0.03	24.70
DY	24.72	−4.83	0.82	2.42	−37.85	0.09	24.63
EP	24.26	−2.91	−0.94	−0.77	−5.46	0.03	24.23
BM	23.24	1.45	1.50 *	0.86	−1.31	0.45	22.79
STR	24.73	−4.90	0.57	−6.97	−7.92	1.34	23.40
LTY	24.18	−2.54	−1.17	−5.41	2.12	0.20	23.98
TMS	23.35	0.95	1.42 *	2.71	0.55	0.00	23.35
DFY	24.18	−2.54	0.52	−3.92	−3.23	0.66	23.52
CRS	23.92	−1.46	−0.14	−4.01	0.27	0.01	23.91
INFL	23.64	−0.28	−0.14	−1.84	0.68	0.04	23.60
IPGR	23.78	−0.83	−1.38	−0.83	−2.29	0.05	23.73
SV	23.59	−0.03	0.10	−0.56	0.20	0.04	23.55

Notes. * indicates significance at the 10% level.

Table 9. Out-of-sample Forecasting Results: Technical Indicators and Principal Components.

Predictor	MSFE	R^2_{OS} (%)	MSFE-Adjusted	$R^2_{OS,EXP}$ (%)	$R^2_{OS,REC}$ (%)	$\bar{(\hat{e})}^2$	Rem. Term
MA(1,5)	23.84	−1.10	−0.83	−1.59	−2.54	0.03	23.81
MA(1,6)	23.82	−1.04	−1.24	−1.20	−2.28	0.04	23.78
MA(2,5)	23.59	−0.04	0.70	0.44	−6.62	0.03	23.56
MA(2,6)	23.80	−0.94	−0.01	−2.79	0.05	0.04	23.77
MA(3,5)	23.48	0.40	1.20	−1.18	4.46	0.03	23.45
MA(3,6)	23.72	−0.58	−0.95	−1.44	1.71	0.04	23.67
MOM(5)	24.50	−3.90	−0.54	−7.15	−3.52	0.04	24.46
MOM(6)	23.89	−1.30	−1.38	−2.58	1.46	0.04	23.85
VOL(1,5)	23.93	−1.47	−1.29	−2.24	−2.38	0.04	23.89
VOL(1,6)	23.70	−0.50	−0.30	−1.67	−0.55	0.04	23.66
VOL(2,5)	23.44	0.57	1.20	−0.30	−2.83	0.04	23.40
VOL(2,6)	23.07	2.15	1.92 **	1.14	1.47	0.04	23.03
VOL(3,5)	23.29	1.21	1.49 *	−1.29	4.35	0.03	23.26
VOL(3,6)	24.01	−1.82	−2.21	−2.71	−2.57	0.04	23.97
PC-ECON (exp)	23.44	0.60	1.38 *	−2.57	4.88	1.42	22.02
PC-ECON (rol)	24.26	−3.10	1.42 *	−6.84	−0.86	0.85	23.41
PC-TECH (exp)	23.61	−0.14	0.54	−1.84	0.85	0.03	23.58
PC-TECH (rol)	25.48	−8.28	−0.78	−9.18	−21.43	0.01	25.47
PC-ALL (exp)	22.93	2.75	2.08 **	0.98	0.82	0.66	22.28
PC-ALL (rol)	23.63	−0.41	1.45 *	−3.27	−1.52	0.11	23.52

Notes. * and ** indicate significance at the 10% and 5% levels, respectively.

However, the PC-ALL model, which integrates the information contained in both macroeconomic variables and technical indicators, delivers the strongest predictive power. It yields the largest positive R^2_{OS} of 2.75%, surpassing all the other R^2_{OS} values in the third column of Tables 8 and 9. Additionally, its *MSFE*-adjusted statistic has also the largest value, confirming that its *MSFE* is significantly lower than that of the historical average benchmark at the 5% level. When evaluating the model's relative predictability across different economic conditions, the PC-ALL model exhibits fairly solid predictability in both

expansions and recessions, as indicated by the positive $R^2_{OS,EXP}$ and $R^2_{OS,REC}$ values in the fifth and sixth columns of Tables 8 and 9.

To address potential overfitting concerns, we compare expanding and rolling window estimations for the PC-ECON, PC-TECH and PC-ALL models in the lower panel of Table 9. As expected, forecasting performance declines under rolling estimation, reflecting the shorter effective sample size and greater sensitivity to structural changes. However, the qualitative ranking of models remains intact: the PC-ALL specification continues to outperform the macro-only and technical-only models. Moreover, the MSFE-adjusted statistics for PC-ALL remain statistically significant under rolling estimation. These findings suggest that the superior performance of the combined information model is not merely driven by in-sample overfitting, although predictive gains become more moderate when parameter estimates are restricted to rolling samples.

In order to assess the value of incorporating information from macroeconomic variables and technical indicators, the forecast encompassing tests can be applied to the PC-ECON and PC-TECH models. Developed by Harvey et al. (1998), these tests determine whether a linear combination of two forecasts yields greater accuracy than either forecast individually. At the 10% significance level, we reject the null hypotheses that either the PC-ECON or PC-TECH forecast encompasses the other, indicating that neither model captures all the available predictive information contained in the other.[2] These findings suggest that combining both macroeconomic variable and technical indicators enhances the predictability of the Korean equity market risk premium.

An alternative approach to analyzing the trade-off between forecasting bias and efficiency, as well as comparing the forecasting performance of principal component predictive regressions with individual predictive regression models, is Theil's (1966) $MSFE$ decomposition. This method breaks down the mean squared forecast errors into the squared forecast bias and a remainder term. The latter term is influenced by the forecast volatility, among other factors, and can be reduced by minimizing the volatility. The overall forecasting performance of a predictive model relies on balancing the reduction in bias and variance.

The seventh and eighth columns of Tables 8 and 9 present the squared forecast bias and remainder term. For the historical average forecast, the squared bias and remainder term are 0.04 and 23.54, respectively. Several forecasting strategies based on individual predictive regression models exhibit relatively small forecast biases, often improving upon the historical average benchmark in this aspect. However, their overall forecasting performance is generally constrained by higher remainder terms, with the exceptions of TMS, MA(3,5) and VOL(3,5). These three variables produce forecasts that exhibit lower bias and greater efficiency than the historical average.

Among all the forecasts in Tables 8 and 9, the PC-ECON forecast has the smallest remainder term of 22.02 in the eighth column, but it has the highest squared bias of 1.42 in the seventh column. On the other hand, the PC-TECH forecast produces a smaller squared bias than the historical average forecast but suffers from a higher remainder term compared to the benchmark. The PC-ALL forecasts, which integrates the information from both the PC-ECON and the PC-TECH forecasts, has a relatively higher bias compared to individual predictive regression models but has the second-lowest remainder term in the eighth column. Consequently, the PC-ALL forecast attains the lowest $MSFE$ value of 22.93 in the second column, significantly outperforming the historical average benchmark at the 5% level. This superior performance is due to a combination of exceptionally low forecast variance, driven by macroeconomic variables, and a relatively small squared bias, supported by technical indicators.

5. Discussion

5.1. Economic Implications of Principal Component Predictive Regression Models

This section discusses the economic implications of principal component predictive regression models, with an analysis of Figures 1–5. First, Panels A–C of Figure 1 depict time series graphs of the estimated principal components of the PC-ECON model in Equation (8), denoted as $\left\{\hat{F}_{k,t}^{ECON}\right\}_{k=1}^{3}$. The panels in Figure 2 report the estimated factor loadings of individual macroeconomic variables associated with each principal component of the PC-ECON model. As shown in Panel A of Figure 2, the first principal component is primarily loaded with STR, LTY and DFY, reflecting common fluctuations in interest rate variables. Meanwhile, other macroeconomic variables such as TMS and CRS load heavily on the third principal component, as seen in Panel C of Figure 2. Consequently, $\hat{F}_{1,t}^{ECON}$, depicted in Panel A of Figure 1, exhibits sharp declines during recessions, while $\hat{F}_{3,t}^{ECON}$, shown in panel C, spikes during recessions and the global financial crisis.

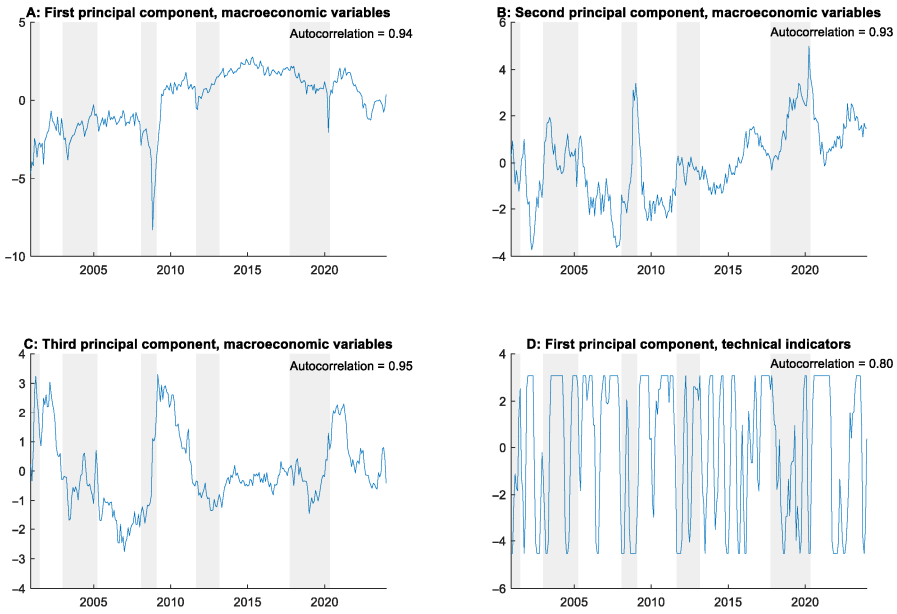


Figure 1. Time-Series Plots of Principal Components for PC-ECON and PC-TECH Models. Gray vertical bar stands for recession periods.

Panel B of Figure 2 reveals that the second principal component is loaded with various macroeconomic variables, including DP, DY, BM, STR and LTY, which enhances its capability to predict future equity risk premium. Accordingly, $\hat{F}_{2,t}^{ECON}$ demonstrates the strongest predictive power, as evidenced by a slope coefficient estimate that is statistically significant at the 5% level in Table 2, which presents the in-sample forecasting results. In line with the findings for U.S. data, the principal component loaded with most of the macroeconomic variables exhibits lower persistence (autocorrelation of 0.93) and outperforms the other principal components, $\hat{F}_{1,t}^{ECON}$ and $\hat{F}_{3,t}^{ECON}$ in our model, in forecasting equity risk premium. Additionally, all three principal components exhibit countercyclical behavior in Panels A-C of Figure 1. This is particularly apparent for $\hat{F}_{2,t}^{ECON}$ and $\hat{F}_{3,t}^{ECON}$, which show distinct local minima near business-cycle peaks and local maxima near troughs. The countercyclical behavior of the principal components is consistent with the empirical evidence that expected equity risk premia vary systematically over the business cycle (Campbell & Thompson, 2008; Ludvigson & Ng, 2007).

Panel D of Figure 2 shows that individual technical indicators almost uniformly load on the single principal component of the PC-TECH model in Equation (8), implying that $\hat{F}_{1,t}^{TECH}$ essentially represents a simple average of 14 technical indicators. As noted by Neely

et al. (2014), $\hat{F}_{1,t}^{TECH}$ acts like a "consensus" indicator, taking either a high or low value as most technical indicators send a buy or sell signal. While the in-sample regression results indicate weak predictive power for the PC-TECH model, Panel D of Figure 1 shows that $\hat{F}_{1,t}^{TECH}$ still captures cyclical movements consistent with the business cycle. Notably, $\hat{F}_{1,t}^{TECH}$ tends to decline rapidly from its highest value to its lowest value around cyclical peaks, while the reverse pattern is observed around cyclical troughs. This pattern is consistent with the view that technical indicators capture gradual price adjustments and short-run return dynamics arising from investor behavior and market frictions (Lo et al., 2000). Additional details on the dominant loadings and the variance explained by each principal component are reported in Appendix A Tables A2 and A3.

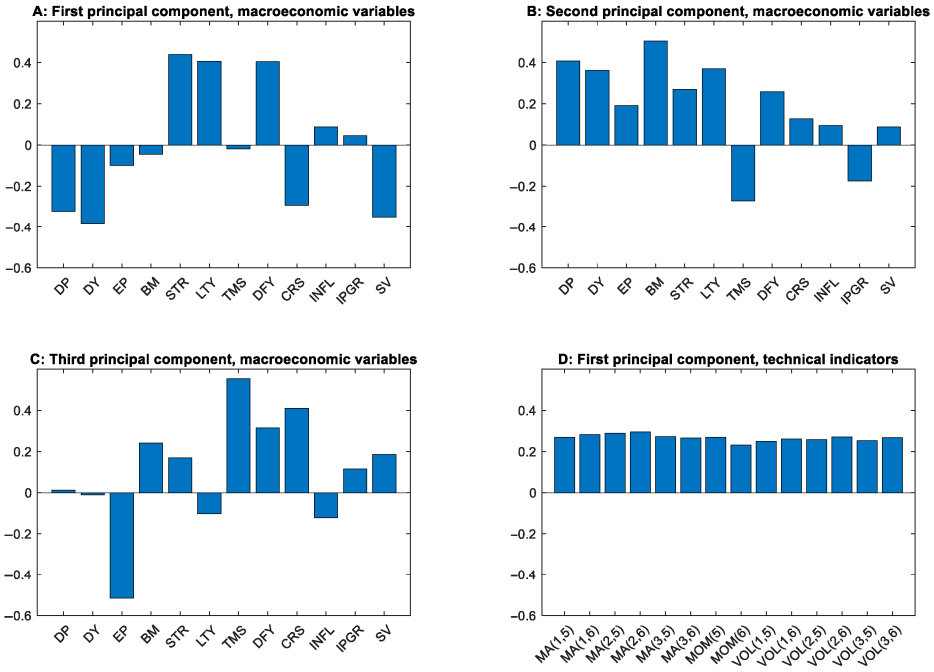


Figure 2. Factor Loadings on Principal Components for PC-ECON and PC-TECH Models.

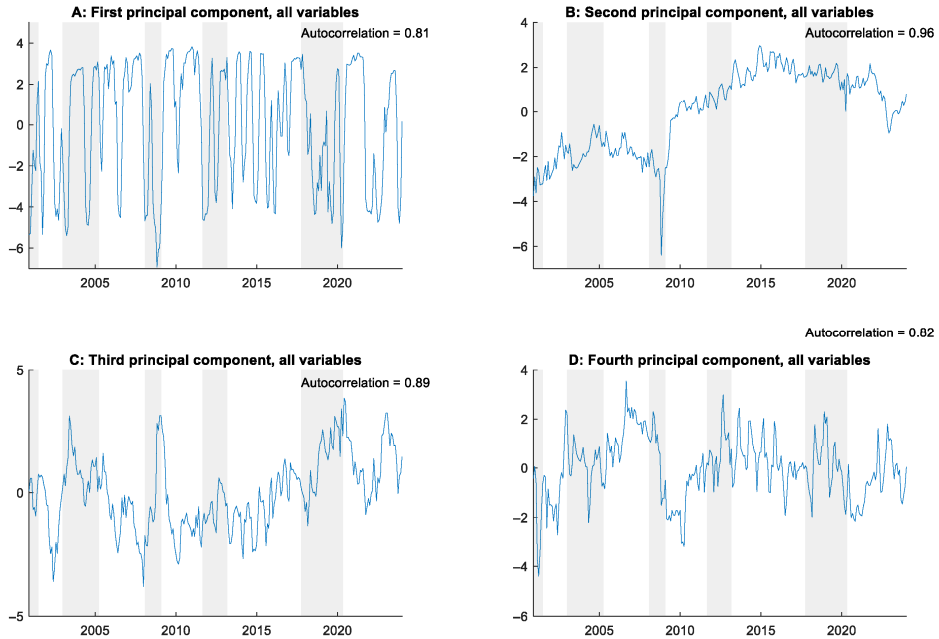


Figure 3. Time-Series Plots of Principal Components for PC-All Model. Gray area stands for recession periods.

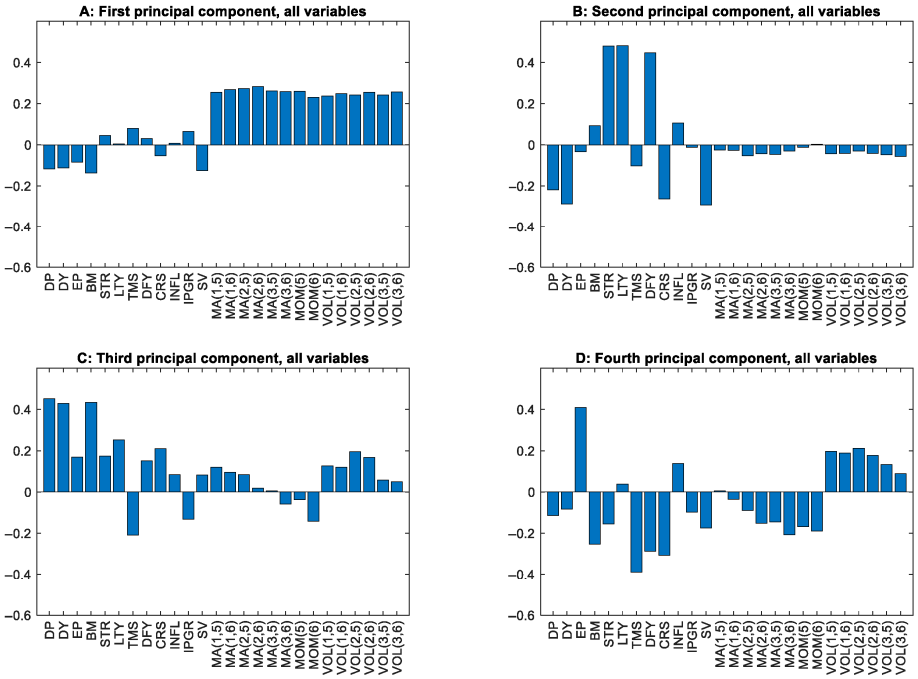


Figure 4. Factor Loadings on Principal Components for PC-ALL Model.

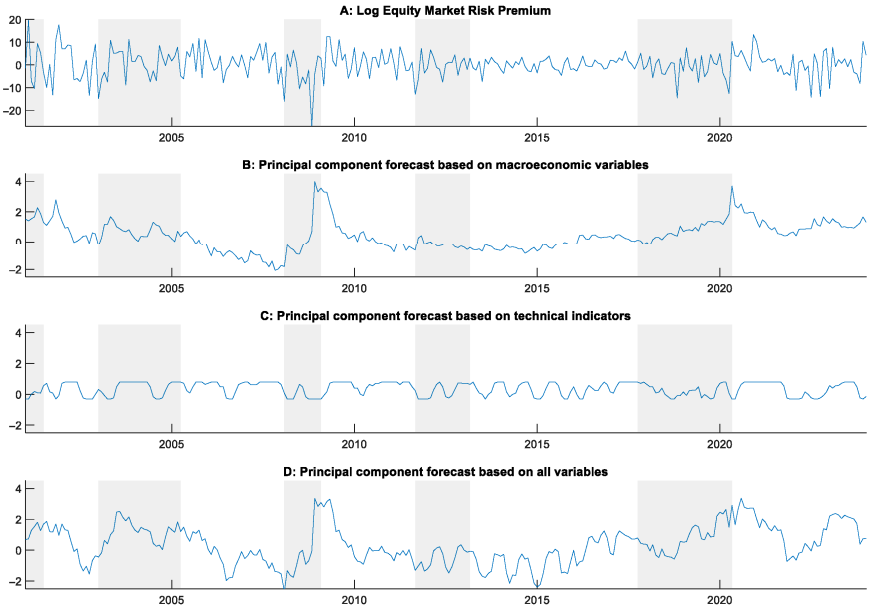


Figure 5. In-sample Log Equity Market Risk Premium Forecasts in Korea based on PC-ALL model. Gray area stands for recession periods.

Figures 3 and 4 present the estimated principal components and factor loadings for the PC-All model in Equation (8). These figures indicate that macroeconomic variables and technical indicators jointly form a complementary relationship, resulting in the principal components derived from the complete set of predictors that closely resemble those obtained separately from either macroeconomic variables or technical indicators alone. Panel A of Figure 4 shows that the first principal component is nearly uniformly loaded with the 14 technical indicators with minimal exposure to macroeconomic variables; as a result, $\hat{F}^{ALL}_{1,t}$ in Panel A of Figure 3 closely resembles $\hat{F}^{TECH}_{1,t}$. Panel B and C of Figures 3 and 4 further illustrate that $\hat{F}^{ALL}_{2,t}$ and $\hat{F}^{ALL}_{3,t}$ are strongly associated with $\hat{F}^{ECON}_{1,t}$ and $\hat{F}^{ECON}_{2,t}$, respectively, as the same macroeconomic variables that exhibit strong loadings on $\hat{F}^{ECON}_{1,t}$ and $\hat{F}^{ECON}_{2,t}$ also exhibit strong loadings on $\hat{F}^{ALL}_{2,t}$ and $\hat{F}^{ALL}_{3,t}$. The last principal component of the PC-ALL

model in Panel D of Figure 4, $\hat{F}^{ALL}_{4,t}$, corresponds to $\hat{F}^{ECON}_{3,t}$ but with opposing signs for each loaded macroeconomic variable. For instance, TMS and CRS, which load heavily on $\hat{F}^{ECON}_{3,t}$, load negatively on $\hat{F}^{ALL}_{4,t}$, whereas EP, which loads heavily on $\hat{F}^{ALL}_{4,t}$, loads negatively on $\hat{F}^{ECON}_{3,t}$. As a result, Panel D of Figure 3 shows that $\hat{F}^{ALL}_{4,t}$ and $\hat{F}^{ECON}_{3,t}$ tend to move in nearly opposite directions, with $\hat{F}^{ALL}_{4,t}$ surging when $\hat{F}^{ECON}_{3,t}$ declines, and vice versa. These relationships are confirmed by the coefficient estimates in Panels C-E of Table 2 where the coefficient estimates on $\hat{F}^{ALL}_{1,t}$, $\hat{F}^{ALL}_{2,t}$ and $\hat{F}^{ALL}_{3,t}$ are similar to those on $\hat{F}^{TECH}_{1,t}$, $\hat{F}^{ECON}_{1,t}$ and $\hat{F}^{ECON}_{2,t}$. Meanwhile, the coefficient estimate on $\hat{F}^{ALL}_{4,t}$ is comparable in magnitude to that on $\hat{F}^{ECON}_{3,t}$, albeit with an opposite sign.

In the PC-ALL model, the first principal component mainly captures common fluctuations in the technical indicators, showing only a weakly association with the macroeconomic variables. The remaining three principal components largely represent comovements within specific groups of macroeconomic variables. Contrary to the findings for U.S. data, the insignificant coefficient estimate for $\hat{F}^{ALL}_{1,t}$ in the PC-ALL model suggests that technical indicators alone provide limited information for forecasting the equity risk premium in the Korean market. Nevertheless, combining technical indicators with macroeconomic variables substantially improves the predictability of equity market risk premium in Korea, as evidenced by the significant in-sample and out-of-sample regression results for the PC-ALL model.

Figure 5 further illustrates the supplementary role of technical indicators for macroeconomic variables. Panel A of Figure 5 shows the actual log equity market risk premium in Korea, while Panels B-D compare in-sample fitted values of the equity risk premium forecasts from the PC-ECON, PC-TECH, and PC-ALL models, respectively. In Panel B, the expected equity risk premium for the PC-ECON model exhibits a relatively smoother countercyclical pattern with respect to the actual equity risk premium in Panel A, which aligns with the factor estimates in Panels A–C of Figure 1. In contrast, Panel C illustrates that the PC-TECH model produces the fitted values with more pronounced cyclical fluctuations, consistent with Panel D of Figure 1. When combining information from both macroeconomic variables and technical indicators in the PC-ALL model, as shown in Panel D, the expected equity risk premium falls more sharply near business-cycle peaks compared to Panel B, and reaches higher values around cyclical troughs than in Panel C. This combined information enhances the countercyclical fluctuations of the expected equity risk premium in the PC-ALL model.

These findings also have broader implications for understanding equity risk premium predictability. From a theoretical perspective, the results suggest that different classes of predictors capture distinct dimensions of variation in expected returns. Macroeconomic variables reflect gradual movements in economic conditions, while technical indicators capture shorter-term market dynamics. The improved performance of the combined model indicates that integrating heterogeneous sources of information can provide a more complete representation of time variation in expected returns.

From a practical perspective, the results suggest that investors and portfolio managers may benefit from combining macroeconomic information with technical indicators when forming forecasts of the equity risk premium. The regime-dependent contribution of technical indicators further suggests that technical signals may be particularly useful during periods of elevated market uncertainty.

5.2. Economic Implications of Forecast Improvements

To provide an economic interpretation of the forecasting improvements, we consider a simple portfolio allocation exercise for a mean-variance investor following Neely et al. (2014). To evaluate the economic value of the forecasts, we compute certainty-equivalent

returns (CER) for a mean-variance investor who allocates wealth between equities and the risk-free asset using forecasts of the equity risk premium. Following Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), and Neely et al. (2014), we conduct a simple asset allocation exercise for a mean-variance investor. Each month, the investor allocates between equities and the risk-free asset using the forecasted equity risk premium $\hat{r}_{t+1}$, with the equity weight set to $w_t = \frac{1}{\gamma}\hat{r}_{t+1}/\hat{\sigma}^2_{t+1}$, where $\gamma = 5$ and $\hat{\sigma}^2_{t+1}$ is estimated from a rolling five-year window of past monthly excess returns. Following Neely et al. (2014), we constrain w_t to lie between 0 and 1.5. Performance is summarized by the monthly Sharpe ratio and the certainty-equivalent return for the portfolio, $CER_p = \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}^2_p$. CER gains are reported relative to the historical average benchmark and are annualized (multiplied by 1200) so that they can be interpreted as an annual portfolio management fee an investor would be willing to pay for access to the forecasting model. We also report CER gains net of transaction costs based on turnover, assuming proportional costs of 50 basis points per trade. Detailed implementation of the asset allocation exercise follows Neely et al. (2014).

Table 10 reports the economic value of the forecasts. The PC-ALL model generates a Sharpe ratio of 0.15, compared with 0.04 for the historical average benchmark or 0.12 for the PC-ECON model. The certainty-equivalent return gain reaches 2.45% per year and remains economically meaningful at 1.24% per year after accounting for transaction costs. These results indicate that combining macroeconomic variables and technical indicators leads to economically significant improvements in portfolio performance for a mean-variance investor.

Table 10. Economic Value of Equity Premium Forecasts.

Forecast Model	Sharpe Ratio	CER Gain (ann. %)	CER Gain (ann. %, 50 bp Cost)
Historical Average	0.04	0.55	0.41
PC-ECON	0.12	0.02	−0.78
PC-TECH	0.05	0.60	−0.78
PC-ALL	0.15	2.44	1.24

Notes. The table reports the economic value of equity premium forecasts for a mean-variance investor with relative risk aversion of 5. CER gains are annualized certainty-equivalent returns relative to the historical average benchmark. For the historical average forecast, the table reports the CER level. Transaction costs of 50 basis points are assumed in the last column.

5.3. Limitations

Despite the economically meaningful evidence of return predictability documented in this study, several limitations should be acknowledged. First, the predictive regressions are based on linear principal component models that summarize information from macroeconomic variables and technical indicators. While this approach provides a parsimonious and transparent framework, it may not fully capture nonlinear relationships or more complex interactions among predictors. There is room for improving predictive performance by introducing more sophisticated models that allow for richer dynamic nonlinear structures.

Second, the results indicate that return predictability varies across market regimes. Although the subsample and dummy-variable analyses partially address structural heterogeneity, the present analysis assumes relatively simple forms of regime variation. Future research could explore models with explicitly time-varying parameters or regime-switching dynamics to better characterize changes in predictability over time.

Third, the analysis is conducted at a monthly frequency, which may not fully capture high frequency market dynamics reflected in technical indicators. Extending the analysis to alternative sampling frequencies may provide additional insights into the interaction between macroeconomic variables and technical indicators.

Fourth, the predictive regression models based on principal components rely on a relatively large set of macroeconomic variables and technical indicators. Although

principal component analysis reduces dimensionality by summarizing information into a small number of factors, the use of a large initial predictor set may still raise concerns about potential data mining. Although this study addresses this concern by using a wild bootstrap *p*-values, future research may explore more parsimonious model specifications or alternative variable selection methods to deal with data mining problems directly.

Finally, although robustness checks based on first-differenced macroeconomic variables suggest that the main results are not driven by persistence, differencing may remove economically meaningful long-run dynamics embedded in macroeconomic levels. Developing predictive regression models that can jointly capture both long-run and short-run dynamics in macroeconomic variables remains an important direction for future research.

6. Conclusions

We investigate the predictive power of technical indicators and macroeconomic variables in forecasting the equity market risk premium in Korea and evaluate whether incorporating technical indicators enhances the predictive power of macroeconomic variables. In contrast to the U.S., where many individual predictors exhibit strong forecasting ability, predictive power of comparable variables in Korea is limited, with only a small number of variables demonstrating statistically significant forecasting power for future equity market risk premium. Nevertheless, our findings indicate that while technical indicators alone may be ineffective or weak predictors, they can substantially improve the forecasting performance of macroeconomic variables. This improvement reflects the fact that technical indicators and macroeconomic variables capture distinct information about business cycles in Korea. As noted by Neely et al. (2014), technical indicators reflect abrupt cyclical movements consistent with business cycles, whereas macroeconomic variables capture relatively smoother countercyclical patterns of the actual equity risk premium. The subsample analysis further indicates that the contribution of technical indicators is regime-dependent, becoming particularly pronounced during periods of financial stress such as the global financial crisis.

Our study contributes to the literature of international stock return predictability by providing an additional evidence that combining information from both technical indicators and macroeconomic variables enhances forecasting accuracy, even when individual predictors have weak predictive power. An important implication of the results is that the role of technical indicators differs across markets. While previous studies based on U.S. and Chinese data find that technical indicators often possess meaningful predictive ability on their own, the Korean evidence indicates that technical indicators are generally weak predictors individually but nevertheless provide economically valuable improvements in predictability when combined with macroeconomic variables. This finding highlights that the complementarity between macroeconomic variables and technical indicators can arise even in markets where technical indicators alone exhibit limited predictive ability.

The results also have practical implications for portfolio management in the Korean equity market. At the monthly horizon, technical indicators provide little predictive value when used in isolation, suggesting that purely technical trading strategies may have limited effectiveness. However, technical indicators become economically useful when combined with macroeconomic information. This finding suggests that asset managers may benefit from integrating technical indicators with macroeconomic variables when constructing forecasting models and dynamic asset allocation strategies.

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Abbreviations

The following abbreviations are used in this manuscript:

ERP	Equity Risk Premium
KOSPI	Korean Composite Stock Price Indexes
CD	Certificate of Deposit
DP	Dividend-price ratio
DY	Dividend yield
EP	Earnings-price ratio
BM	Book-to-market ratio
STR	Short-term interest rate
LTY	Long-term interest rate
TMS	Term spread
DFY	Default yield spread
CRS	Credit spread
INFL	Inflation
CPI	Consumer price index
IPGR	Industrial production growth rate
SV	Stock variance
MA	Moving-average
OLS	Ordinary least squared
MSFE	Mean squared forecast error

Appendix A

Table A1. Descriptions of Macroeconomic Variables.

Variables	Descriptions
Dividend-price ratio	Log of the ratio between annual dividends (monthly averaged) and the KOSPI index level
Dividend yield	Log of cash dividends from the previous month relative to lagged KOSPI prices
Earnings-price ratio	Log of the ratio of lagged earnings to contemporaneous KOSPI prices
Book-to-market ratio	Log of the aggregate book value relative to market value for the KOSPI
Short-term interest rate	Yield on a 91-day CD
Long-term interest rate	Yield on 10-year Korean government bonds
Term spread	Yield spread between long-term government bonds and the short-term interest rate
Default yield spread	Yield spread between BBB- and AA-rated corporate bonds
Credit spread	Difference between AA-rated corporate bond yields and long-term interest rate

Table A1. *Cont.*

Variables	Descriptions
Inflation	Monthly inflation rate derived from the consumer price index for all urban households
Industrial production growth rate	Monthly growth rate computed from the industrial production index
Stock variance	um of squared daily KOSPI returns within each month

Notes: Considering publication lags of the CPI and the industrial production index, INFL and IPGR are computed using two-month lags to ensure that the information would have been publicly available at the time forecasts are formed.

Table A2. Variance Explained by Principal Components.

Predictor	Eigenvalue	Explained (%)	Cumulative (%)
Panel A. Based on Macroeconomic Variables			
$\hat{F}_1^{ECON}$	3.42	28.50	28.50
$\hat{F}_2^{ECON}$	2.52	21.01	49.51
$\hat{F}_3^{ECON}$	1.62	13.49	63.00
Panel B. Based on Technical Indicators			
$\hat{F}_1^{TECH}$	8.82	63.00	63.00
Panel C. Based on All Variables			
$\hat{F}_1^{ALL}$	9.43	36.26	36.26
$\hat{F}_2^{ALL}$	3.26	12.55	48.81
$\hat{F}_3^{ALL}$	2.29	8.79	57.61
$\hat{F}_4^{ALL}$	1.69	6.50	64.11

Notes: This table reports the eigenvalues and the proportion of variance explained by each principal component. Principal components are extracted from standardized predictor variables.

Table A3. Dominant Loadings of Principal Components.

Predictor	Variable	Loading	Variable	Loading
Panel A. Based on Macroeconomic Variables				
$\hat{F}_1^{ECON}$	STR	0.44	DFY	0.40
	LTY	0.41	DY	−0.38
$\hat{F}_2^{ECON}$	BM	0.50	LTY	0.37
	DP	0.41	DY	0.36
$\hat{F}_3^{ECON}$	TMS	0.55	CRS	0.41
	EP	−0.52	DFY	0.31
Panel B. Based on Technical Indicators				
$\hat{F}_1^{TECH}$	MA(2,6)	0.30	MA(1,6)	0.28
	MA(2,5)	0.29	MA(3,5)	0.27
Panel C. Based on All Variables				
$\hat{F}_1^{ALL}$	MA(2,6)	0.28	MA(1,6)	0.27
	MA(2,5)	0.27	MA(3,5)	0.26
$\hat{F}_2^{ALL}$	LTY	0.48	DFY	0.45
	STR	0.48	SV	−0.29
$\hat{F}_3^{ALL}$	DP	0.45	DY	57.61
	BM	0.43	LTY	0.25
$\hat{F}_4^{ALL}$	EP	0.41	CRS	−0.29
	TMS	−0.39	DFY	−0.29

Notes

[1] Using the wild bootstrap procedure, we generate a pseudo sample for the equity risk premiums and the predictive regressors. The wild bootstrap approach retains the contemporaneous correlations in the data, accommodates general forms of conditional heteroskedasticity, and preserves the persistence properties of the predictive regressors (Neely et al., 2014).

[2] The complete test results are omitted for brevity and available on request.

References

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *Journal of Finance*, *68*, 929–985. [CrossRef]

Atmaz, A., Gulen, H., Cassella, S., & Ruan, F. (2024). Contrarians, extrapolators, and stock market momentum and reversal. *Management Science*, *70*, 5949–5984. [CrossRef]

Bae, S. C., Min, J. H., & Jung, S. (2011). Trading behavior, performance, and stock preference of foreigners, local institutions, and individual investors: Evidence from the Korean stock market. *Asia-Pacific Journal of Financial Studies*, *40*, 199–239. [CrossRef]

Bai, J. (2003). Inferential theory for factor models of large dimensions. *Econometrica*, *71*, 135–171. [CrossRef]

Bessembinder, H., & Chan, K. (1998). Market efficiency and the returns to technical analysis. *Financial Management*, *27*, 5–17. [CrossRef]

Blume, L., Easley, D., & O'hara, M. (1994). Market statistics and technical analysis: The role of volume. *Journal of Finance*, *49*, 153–181. [CrossRef]

Breen, W., Glosten, L. R., & Jagannathan, R. (1989). Economic significance of predictable variation in stock index returns. *Journal of Finance*, *44*, 1177–1189. [CrossRef]

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, *47*, 1731–1764. [CrossRef]

Campbell, J. Y. (1987). Stock returns and the term structure. *Journal of Financial Economics*, *18*, 373–399. [CrossRef]

Campbell, J. Y., Grossman, S. J., & Wang, J. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics*, *108*, 905–939. [CrossRef]

Campbell, J. Y., & Shiller, R. J. (1988a). Stock prices, earnings, and expected dividends. *Journal of Finance*, *43*, 661–676. [CrossRef]

Campbell, J. Y., & Shiller, R. J. (1988b). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies*, *1*, 195–228. [CrossRef]

Campbell, J. Y., & Shiller, R. J. (1998). Valuation ratios and the long-run stock market outlook. *Journal of Portfolio Management*, *24*, 11–26. [CrossRef]

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, *21*, 1509–1531. [CrossRef]

Chamberlain, G., & Rothschild, M. (1983). Arbitrage, factor structure, and mean-variance analysis on large asset markets. *Econometrica*, *51*, 1281–1304. [CrossRef]

Chun, S. (2021). Forecasting the equity risk premium in the Korean stock market: A factor analysis approach. *Global Business & Finance Review*, *26*, 77–89. [CrossRef]

Clark, T. E. (2004). Can out-of-sample forecast comparisons help prevent overfitting? *Journal of Forecasting*, *23*, 115–139. [CrossRef]

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, *138*, 291–311. [CrossRef]

Conrad, J., & Kaul, G. (1998). An anatomy of trading strategies. *Review of Financial Studies*, *11*, 489–515. [CrossRef]

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, *25*, 383–417. [CrossRef]

Fama, E. F., & Blume, M. (1966). Filter rules and stock market trading. *Journal of Business*, *39*, 226–241.

Fama, E. F., & French, K. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, *22*, 3–25. [CrossRef]

Fama, E. F., & French, K. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, *25*, 23–49. [CrossRef]

Fama, E. F., & Schwert, G. W. (1977). Asset returns and inflation. *Journal of Financial Economics*, *5*, 115–146. [CrossRef]

Ferreira, M. A., & Santa-Clara, P. (2011). Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics*, *100*, 514–537. [CrossRef]

Gao, L., Han, Y., Li, S. Z., & Zhou, G. (2018). Market intraday momentum. *Journal of Financial Economics*, *129*, 394–414. [CrossRef]

Gervais, S., Kaniel, R., & Mingelgrin, D. H. (2001). The high-volume return premium. *Journal of Finance*, *56*, 877–919. [CrossRef]

Goyal, A., & Welch, I. (2003). Predicting the equity premium with dividend ratios. *Management Science*, *49*, 639–654. [CrossRef]

Granville, J. E. (1963). *Granville's new key to stock market profits*. Prentice Hall.

Griffin, J. M., Harris, J. H., & Topaloglu, S. (2003). The dynamics of institutional and individual trading. *Journal of Finance*, *58*, 2285–2320. [CrossRef]

Grinblatt, M., & Titman, S. (1989). Mutual fund performance: An analysis of quarterly portfolio holdings. *Journal of Business*, *62*, 393–416. [CrossRef]

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review*, *85*, 1088–1105. [CrossRef]

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, *48*, 1433–1461. [CrossRef]

Harvey, D. I., Leybourne, S. J., & Newbold, P. (1998). Tests for forecast encompassing. *Journal of Business & Economic Statistics*, *16*, 254–259. [CrossRef]

Huang, D., Li, J., Wang, L., & Zhou, G. (2020). Time series momentum: Is it there? *Journal of Financial Economics*, *135*, 774–794. [CrossRef]

Inoue, A., & Kilian, L. (2005). In-sample or out-of-sample tests of predictability: Which one should we use? *Econometric Reviews*, *23*(4), 371–402.

James, F. E., Jr. (1968). Monthly moving averages—An effective investment tool? *Journal of Financial and Quantitative Analysis*, *3*, 315–326. [CrossRef]

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *48*, 65–91. [CrossRef]

Jensen, M., & Benington, G. (1970). Random walks and technical theories: Some additional evidence. *Journal of Finance*, *25*, 469–482. [CrossRef]

Kang, D., Ryu, D., & Webb, R. I. (2025). Momentum and reversal effects in the Korean stock market. *Investment Analysts Journal*, *54*, 611–627. [CrossRef]

Kaniel, R., Ozoguz, A., & Starks, L. (2012). The high volume return premium: Cross-country evidence. *Journal of Financial Economics*, *103*, 255–279. [CrossRef]

Kim, M. H., Kim, Y. M., & Yang, K. (2022). Understanding BOXPI—Industry portfolio perspectives. *Journal of Asian Economics*, *81*, 101500. [CrossRef]

Kothari, S. P., & Shanken, J. (1997). Book-to-market, dividend yield, and expected market returns: What do the data tell us? *Review of Financial Studies*, *9*, 1033–1059. [CrossRef]

Lee, C. M. C., & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance*, *55*, 2017–2069. [CrossRef]

Levy, R. A. (1967a). Random walks: Reality or myth. *Financial Analysts Journal*, *23*, 69–77. [CrossRef]

Levy, R. A. (1967b). Relative strength as a criterion for investment selection. *Journal of Finance*, *22*, 595–610. [CrossRef]

Liu, W., Zheng, J., Chen, J., & Chen, W. (2025). Evaluating the inclusion of technical indicators for deep learning-empowered stock price prediction in the Chinese market. In J. Hedman, R. Gleasure, & M. Bandara (Eds.), *Enterprise applications, markets and services in the finance industry* (FinanceCom 2024. Lecture notes in business information processing, Vol. 541). Springer. [CrossRef]

Lo, A., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance*, *4*, 1705–1765. [CrossRef]

Ludvigson, S. C., & Ng, S. (2007). The empirical risk-return relation: A factor analysis approach. *Journal of Financial Economics*, *83*, 171–222. [CrossRef]

Menkhoff, L. (2010). The use of technical analysis by fund managers: International evidence. *Journal of Banking and Finance*, *34*, 2573–2586. [CrossRef]

Ming-Ming, L., & Siok-Hwa, L. (2006). The profitability of the simple moving averages and trading range breakout in the Asian stock markets. *Journal of Asian Economics*, *17*, 144–170. [CrossRef]

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, *104*, 228–250. [CrossRef]

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science*, *7*, 1772–1791. [CrossRef]

Nelson, C. R. (1976). Inflation and the rates of return on common stock. *Journal of Finance*, *31*, 471–483. [CrossRef]

Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance*, *53*, 1775–1798. [CrossRef]

Park, J., & Kim, M. (2014). Investment performance of individual investors: Evidence from the Korean stock market. *Emerging Markets Finance and Trade*, *50*, 194–211. [CrossRef]

Pontiff, J., & Schall, L. D. (1998). Book-to-market ratios as predictors of market returns. *Journal of Financial Economics*, *49*, 141–160. [CrossRef]

Rouwenhorst, K. G. (1998). International momentum strategies. *Journal of Finance*, *53*, 267–284. [CrossRef]

Rozeff, M. S. (1984). Dividend yields are equity risk premiums. *Journal of Portfolio Management*, *11*, 68–75. [CrossRef]

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance*, *40*, 777–790. [CrossRef]

Stock, J. H., & Watson, M. W. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics*, *20*, 147–162. [CrossRef]

Sun, M., & Glabadanidis, P. (2022). Can technical indicators predict the Chinese equity risk premium? *International Review of Finance*, *22*, 114–142. [CrossRef]

Theil, H. (1966). *Applied economic forecasting. Studies in mathematical and managerial economics*. North-Holland.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, *21*, 1455–1508. [CrossRef]

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