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Forecasting the Equity Risk Premium in the Korean Stock Market: A Factor Analysis Approach

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A B S T R A C T

Purpose: This article investigates stock return predictability in the Korean stock market using the methodology of dynamic factor analysis.
Design/methodology/approach: This article collects monthly data on the equity risk premium on the KOSPI and twelve financial and macroeconomic variables spanning from October 2000 to December 2020 and evaluates the forecasting performance of the dynamic factor predictive regression model by comparing in-sample and out-of-sample predictability with those of individual predictors.
Findings: The article finds that the dynamic factor predictive regression exhibits statistically and economically significant in-sample predictability for the future equity risk premium for the KOSPI, as strongly as the best individual predictor can do. Also, the dynamic factor approach can outperform the benchmark historical average in out-of-sample predictability. The detailed analysis of the diffusion indexes reveals that each factor captures different information from various financial and macroeconomic variables relevant for return prediction and the diffusion indexes can deliver better forecasts of the future equity risk premium.
Research limitations/implications: There exist different regression methods to combine forecasts comparable to the dynamic factor predictive model such as the forecast combination method by Rapach et al. (2010) and the bagging method by Inoue and Kilian (2008) and Jordan et al. (2017). The study proposes to compare the performance of these models with that of the dynamic factor predictive model in the Korean stock market as future research.
Originality/value: The article is the first attempt to apply the dynamic factor predictive regression model to a large set of financial and macroeconomic data in Korea and evaluate its in-sample and out-of-sample predictability in comparison to those of individual predictive variables.

Keywords: Equity risk premium predictability in Korea, Financial and macroeconomic variables, Dynamic factor predictive regression, In-sample predictability, Out-of-sample forecasts

I. Introduction

There have been numerous studies attempting to identify the variables that are capable of forecasting the future equity risk premium and suggesting evidence of stock return predictability using economic variables such as financial ratios comprising accounting measure of cash flows scaled by prices, or macroeconomic variables proxying the state of the economy. These variables include dividend-price ratio, earnings-price ratio, book-to-market, nominal interest rates and their spreads, inflation, and so on.

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The evidence of stock return predictability based on financial and macroeconomic variables is largely supported by in-sample predictive regression models using the U.S. data, which at the same time raises several methodological concerns. For example, Welch and Goyal (2008) re-examine the predictability of a large number of well-known predictors using updated data to find that most of the variables are no longer able to predict the future stock returns even in-sample, and they have shown poor out-of-sample performance with respect to a simple forecast based on the historical average of returns. There is also a data mining problem, which arises when a researcher searches through the data without accounting for the number of searches in performing statistical inference. As suggested by Foster et al. (1997) and Ferson et al. (2003), if an independent variable arises as a predictor from the collective search through the data, it would have no predictive power in the future. While several researchers including White (2000) and Inoue and Kilian (2005) propose a testing procedure using the maximal statistics to address the data mining problem in the statistical inference, the procedure only addresses which variable is the best predictor and may miss the important information contained in other variables to predict the future equity premium.

This article investigates stock return predictability in the Korean stock market using the methodology of dynamic factor analysis adopted by Stock and Watson (2002), Ludvigson and Ng (2007) and Neely et al. (2014). The dynamic factor model estimates a small number of factors from a large number of economic variables by principal component analysis and constructs the forecasts of future stock returns using the estimated factors. These factors are called as diffusion indexes by Stock and Watson (2002), measuring common fluctuations in the potential predictors. Thus, by summarizing the information from a large set of economic variables, the factor structure is likely to generate a more reliable signal to predict the future equity premium than does any single variable.

This study evaluates the forecasting performance of diffusion indexes for future stock returns by comparing its in-sample and out-of-sample predictability with those of individual financial and macroeconomic variables. As noted by Rapach and Wohar (2006) and Welch and Goyal (2008), out-of-sample tests provide one of the effective statistical measures to guard against data mining by replicating the real practice of estimating a forecasting model using past in-sample data to predict out-of-sample observations that are not used in the estimation. The study also adopts a wild bootstrap procedure to perform the in-sample and out-of-sample inference to account for the persistence and the unknown covariance structure of the variables.

This article contributes to the literature on the international stock return predictability by studying the Korean stock market to shed light on the early evidence of stock return predictability found in the U.S. data. There are several studies including Rangvid et al. (2014) and Charles et al. (2017) to investigate the international stock return predictability including Korea but they are limited to testing the predictability of individual variables. Jordan et al. (2017) adopt the bagging method to combine forecasts from multiple predictors based on the bootstrap and investigates its out-of-sample predictability using the international data including Korea. However, they find that the bagging method underperforms the benchmark historical average of stock returns in Korea and fail to provide improvements in predictability. In this paper, the dynamic factor model is employed to construct diffusion indices taking advantage of the information contained in twelve financial and macroeconomic variables, and thus its predictive power is compared to that of individual predictors using both in-sample and out-of-sample tests.

The study uses monthly data spanning from October 2000 to December 2020 for twelve popular financial and macroeconomic variables in Korea and the equity risk premium for the aggregate Korean stock market. The empirical results suggests that both in-sample and out-of-sample predictability of the dynamic factor predictive regression model is statistically and economically significant and its predictive power is as strong as that of the best predictive regression model with individual predictor. The diffusion indexes employed in the predictive regression capture important information from 12 financial and macroeconomic variables relevant for return prediction and helps to deliver better forecasts of the future equity risk premium for the KOSPI.

The rest of the paper is organized as follows. Section

2 presents a literature review and Section 3 describes the data and introduces the predictive regression models along with in-sample and out-of-sample tests. Section 4 presents the empirical results and provides economic implications of diffusion indexes for stock return predictive regressions. Section 5 presents the conclusions and offers implications for future research.

II. Literature Review

A. Stock return predictability and methodological issues

As described by Fama (1970), stock return predictability based on financial and macroeconomic variables reflects the view of efficient capital market in which expected returns change over time in accordance with the economic state variables. Subsequent studies perform extensive empirical researches primarily based on the U.S. data and support this view employing dividend-price ratio (Rozeff (1984), Campbell and Shiller (1988a, 1998), Fama and French (1988, 1989)), earnings-price ratio (Campbell and Shiller (1988b, 1998)), book-to-market ratio (Kothari and Shanken (1997), Pontiff and Schall (1998)), nominal interest rates (Fama and Schwert (1977), Breen et al. (1989)), term and default spreads (Campbell (1987), Fama and French (1989)), and inflation (Nelson (1976), Campbell and Vuolteenaho (2004)).

Although these variables exhibit good in-sample predictive power, several methodological issues have been raised by many researchers. Nelson and Kim (1993) and Stambaugh (1999) show that small-sample bias can occur in the slope coefficient estimator for the predictive variables when the potential regressors are highly autocorrelated and correlated with the past regression error terms. They show that this bias may lead to substantial size distortions in testing the null hypothesis of no predictability. Moreover, the evidence of in-sample predictability does not guarantee the out-of-sample predictability; Bossaert and Hillion (1999) implement the model selection criteria to prevent data mining and examine international stock return predictability in 14 countries to discover that the presence of in-sample predictability does not lead to any significant out-of-sample predictability. Welch and Goyal (2008) select a large number of economic variables that have shown good predictive power and re-examine their performance to find that most regression models perform poorly in both in-sample and out-of-sample. In addition, the regression models with individual predictors are subject to the data mining concerns raised by Foster et al. (1997) and Ferson et al. (2003). Foster et al. (1997) provide the theoretical framework of data mining in predicting returns and show that usual test statistics can be inflated to reject the null hypothesis of no predictability for independent regressors if we fail to account for the number of searches in a large set of potential regressors. Ferson et al. (2003) show that the data mining problem can be even worse as we adopt highly persistent regressors in the regression and many of the regressions in the literature based on individual variables may be spurious.

In order to guard against data mining and improve upon forecasting performance by individual predictors, this study adopts a predictive regression model based on a small number of principal components extracted from a large number of financial and macroeconomic variables relying on a dynamic factor model and evaluates its forecasting performance using both in-sample and out-of-sample tests. In addition, the study performs the in-sample and out-of-sample inferences based on the wild bootstrap procedure to overcome the small sample bias, and thus potential size distortions.

It should be noted that there exist a few other regression methods to combine forecasts from multiple predictive variables. For example, Rapach et al. (2010) propose a forecast combination method in which the equity premium is computed in the form of a weighted average of the individual forecasts with different weighting methods. There is another forecast combination method called the bagging proposed by Inoue and Kilian (2008) that utilizes a large number of bootstrap resampling to average the forecasts selected by the pretest on each bootstrap sample. Jordan et al. (2017) apply the bagging method to examine the out-of-sample forecasting ability in the G7 and eleven Asian countries, and find that bagging generally improves forecasting accuracy. Among these

forecast combination methods, Oueslati and Hammami (2017) suggest that the dynamic factor predictive model is the best forecasting method after comparing the performance of different forecasting methods to predict the market excess returns in Saudi Arabia and Malaysia. Although it is still worth comparing these models' performance in the Korean stock market, this study focuses on the forecasting performance of the dynamic factor predictive regression model and leave the issues of comparing performance for different forecast combination methods in the Korean stock market for future research.

B. Return predictability in the international equity markets

Return predictability in global stock markets has also been explored by many financial economists, such as Rapach et al. (2005), Hjalmarsson (2010), Schrimpf (2010), Jordan et al. (2014), Charles et al. (2017), and Jordan et al. (2017). Rapach et al. (2005) examine the stock return predictability in twelve industrialized countries using nine major macroeconomic variables by testing both in-sample and out-of-sample tests. They find that interest rates are the most consistent and reliable predictors for many countries. Hjalmarsson (2010) investigates the predictability of four common variables, dividend-price ratio, earnings-price ratio, short-term interest rate and term spread, for 24 developed and 16 emerging markets. By applying the panel data regression methods, he finds that the short-term interest rate and the term spread are robust predictors for developed markets. Meanwhile, Schrimpf (2010) investigates the return predictability of five major stock markets with accounting for model uncertainty using nine financial and macroeconomic variables and concludes that only very few variables can be identified as robust predictors.

Recently, Jordan et al. (2014) conduct both in-sample and out-of-sample tests upon various financial and macroeconomic variables to provide new evidence of predictability for smaller equity markets in 14 European countries. They suggest that a simple forecast procedure using a combination of univariate models can improve the forecast accuracy. Charles et al. (2017) investigate stock return predictability in 16 Asia-Pacific and 21 European stock markets by applying the improved augmented regression method with wild bootstrapping for financial ratios, technical indicators and short-term interest rates. They find that the price pressure and interest rate exhibit strong predictive power with satisfactory out-of-sample forecasting performance. Jordan et al. (2017)'s work is closely related and comparable to this paper in that they investigate the out-of-sample predictability of a forecasting combination method called as the bagging for the G7 and eleven Asian countries including Korea. However, they find that predictability of individual regression forecasts is weak in several Asian markets including Korea and the bagging method fails to provide substantial improvements in predictability in Korea.

C. Return predictability in Korean stock market

For the Korean stock market, early studies find that the earnings-price ratio has significant predictive power for the aggregate stock returns. Kim and Kim (2004) and Chung and Kim (2010) apply the *t*-test proposed by Lewellen (2004) to account for the finite sample bias in predictive regressions and find that the earning-price ratio among a few financial ratio variables and short-term interest rate can predict the future stock returns. Jeong (2012) investigates the long-run predictability of Korean stock market and finds that dividend yield and earnings-price ratio along with past stock returns can predict the future stock returns in Korea.

More recently, Chun (2020) and Chun (2021) consider a large set of financial and macroeconomic variables to predict the future stock returns. Chun (2020) employs both in-sample and out-of-sample tests based on the bootstrapping procedure to account for the finite sample bias and suggests that the book-to-market ratio arises as a consistent and significant predictor for the KOSPI returns in the recent data. Chun (2021) applies the maximal *t*-statistics to control for the data mining effects and finds a mixed evidence of predictability that while there is no significant predictor for the aggregate KOSPI returns once controlling for the data mining effect, the book-to-market ratio and the dividend-price ratio exhibit limited

predictive power for size portfolio returns.

As stated above, there have been many studies to investigate the individual variable's predictive power for the Korean stock market returns but this research firstly aims to apply a dynamic factor analysis that can summarize and take advantage of all the information contained in a large set of predictive variables in Korea. By comparing its in-sample and out-of-sample predictability with those of individual predictors, this study evaluates the capacity of financial and macroeconomic variables as a whole to directly forecast the future stock returns.

III. Data and Empirical Methods

A. Data

The research uses monthly data spanning from October 2000 to December 2020, obtained from the Statistics Korea and the Bank of Korea Economic Statistics System. The equity risk premium is the difference between the log return on the Korean Composite Stock Price Indexes (KOSPI) and the log return on a risk-free rate proxied by the interest rate on a 91-day CD. The set of financial and macroeconomic variables are constructed following the previous literature to predict the future equity risk premium:

1. Dividend-price ratio (log), DPR: log of a monthly average of annual dividends minus the log of stock prices on the KOSPI.
2. Dividend yield (log), DYR: log of previous-month cash dividends minus the log of lagged stock prices on the KOSPI.
3. Earnings-price ratio (log), EPR: log of previous-month earnings minus the log of stock prices on the KOSPI.
4. Book-to-market ratio (log), BMR: log of book-to-market value ratio for the KOSPI.
5. Short-term interest rate, STR: interest rate on a 91-day CD.
6. Long-term interest rate, LTR: long-term government bond yield (10-year).
7. Term spread, TMS: difference between long-term yield and short-term interest rate.
8. Default yield spread, DFS: difference between BBB- and AA-rated corporate bond yields.
9. Credit spread, CRS: difference between AA-rated corporate bond yields and long-term interest rate.
10. Inflation, IFL: calculated from the CPI for all urban consumers.
11. Industrial production growth rate, IPG: calculated from the industrial production index.
12. Stock variance, SVR: monthly sum of squared daily returns on the KOSPI.

Table 1 presents summary statistics for the log equity risk premium and 12 financial and macroeconomic variables for October 2000 to December 2020. The average monthly equity risk premium is 0.447% and its monthly standard deviation is 5.949%, so that they produce a monthly Sharpe ratio of 0.075. Many macroeconomic variables exhibit highly persistent autocorrelations, particularly for the interest rates and interest rate spreads.

B. Empirical methods

1. In-sample analysis and univariate predictive regressions

To explore the predictability of future equity risk premium, researchers frequently employ the following univariate regression model:

$$r_{t+1} = \alpha_i + \beta_i z_{i,t} + \epsilon_{i,t+1}, \quad (1)$$

where r_{t+1} denotes the return on the KOSPI in excess of the risk-free rate from period t to t+1, $z_{i,t}$, $i = 1, \cdots, 12$, denotes a predictive variable at time t, and $\epsilon_{i,t+1}$ is the regression disturbance term. Stock return predictability can be tested by establishing the null hypothesis of no predictability, $\beta_i = 0$, and this paper imposes a one-sided alternative hypothesis according to the theory of financial economics, as is recommended by Inoue and Kilian (2005) to increase the power of in-sample predictability tests. Therefore, this paper defines each regressor $z_{i,t}$

Table 1. Summary Statistics, October 2000 to December 2020

Variable	Mean	Standard Deviation	Min	Max	Auto-correlation	Sharpe ratio
Risk Premium	0.447	5.949	-26.774	19.698	0.033	0.075
DPR	-4.139	0.249	-4.605	-3.555	0.939	
DYR	-4.122	0.253	-4.585	-3.561	0.945	
EPR	1.933	0.318	0.660	2.635	0.882	
BMR	4.544	0.179	3.980	5.002	0.923	
STR (ann %)	3.193	1.451	0.630	6.990	0.972	
LTR (ann %)	4.046	1.661	1.254	7.860	0.976	
TMS (ann %)	0.852	0.749	-0.500	2.960	0.954	
DFS (ann %)	5.001	1.271	2.140	6.408	0.989	
CRS (ann %)	0.754	0.555	0.224	4.380	0.953	
IFL (%)	0.185	0.371	-0.745	1.188	0.275	
IPG (%)	0.263	1.354	-4.332	4.750	-0.287	
SVR	0.004	0.006	0.000	0.062	0.478	

Notes. The log equity risk premium, IFL and IPG are measured in percent, and STR, LTR, TMS, DFS, CRS are measured in annual percent. The Sharpe ratio is measured as the monthly average of the log equity risk premium divided by its monthly standard deviation.

to have its slope coefficient β_i positive under the alternative hypothesis and tests $H_0: \beta_i = 0$ against $H_A: \beta_i > 0$ using the ordinary least squares (OLS) estimate of β_i in Eq. (1).

The OLS estimator for β_i in Eq. (1) may be biased if the predictor is highly persistent and correlated with past regression error terms, which leads to inflate the test statistics and incur size distortion to favor predictability. In order to overcome this problem, this study adopts a wild bootstrap procedure used in Neely et al. (2014) to compute *p*-values that can account for the persistence in predictors and the variance-covariance structure among the variables, and computes the test statistics using a heteroskedasticity-consistent standard error estimator.[1)]

2. Predictive regressions using a dynamic factor model

The dynamic factor model, or the diffusion index has been adopted by Stock and Watson (2002), Ludvigson and Ng (2007) and Neely et al. (2014) to extract information from numerous financial and macroeconomic variables for predictive regressions by estimating latent factors using principal components. Let $Z_t = (Z_{1,t}, \cdots, Z_{N,t})'$ denote the *N*-vector of the entire set of financial and macroeconomic variables (in this case, N = 12), the diffusion indexes can be obtained by estimating the following dynamic factor model:

$$Z_t = \lambda' f_t + e_t, \tag{2}$$

where f_t and λ. are the *K*-vectors of latent factors and factor-loadings, respectively, and e_t is the *N*-vector of error terms. A strict factor model can be applied to estimate the Eq. (2) when these error terms are assumed to be uncorrelated, which is unlikely in practice. Chamberlain and Rothschild (1983) and Bai (2003) propose an approximate factor model with the less strict assumption that the error terms are allowed to be serially correlated and heteroskedastic. The Eq. (2) allows to capture co-movements in the

1) This paper follows the wild bootstrap procedure adopted by Neely et al. (2014), which can produce a pseudo sample of observations for the equity risk premiums and the 12 predictive variables. The wild bootstrap procedure can preserve the contemporaneous correlations in the data and account for general forms of conditional heteroskedasticity along with capturing the adequate persistence in the predictive variables. (See Neely et al. (2014) for the details.)

predictors through the latent factors.

The latent factors in Eq. (2) can be consistently estimated by principal component analysis (Bai (2003)). Then, the estimated latent factors, or the diffusion indexes can be adopted as regressors in the following predictive regression:

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{f}_{k,t} + \epsilon_{t+1}. \quad (3)$$

Instead of using all the individual predictors in the predictive regressions that may also contain noisy signals, diffusion indexes in Eq. (3) parsimoniously identify the important common fluctuations in a large number of predictors and deliver relevant information for return prediction. In Eq. (3) it is important to determine the number of factors, K, to keep the regression model parsimonious. This paper follows Neely et al. (2014) to choose $K = 3$ by the adjusted-R^2. To conduct inference for predictability, this research computes the OLS estimator for β_k in Eq. (3) along with heteroskedasticity-consistent standard error estimator and construct the t-statistics to compare with wild bootstrapped p-values.

3. Out-of-sample analysis and forecast evaluation

For the out-of-sample tests, this study firstly splits the total sample of T observations into two sub-periods of an in-sample portion composed of the first R observations and an out-of-sample portion composed of the last $Q = T - R$ observations. The initial out-of-sample forecast of the equity risk premium for an individual predictive variable in Eq. (1) is obtained as follows:

$$\hat{r}_{R+1} = \hat{\alpha}_{R,i} + \hat{\beta}_{R,i} z_{R,i}, \quad (4)$$

where $\hat{\alpha}_{R,i}$ and $\hat{\beta}_{R,i}$ are the OLS estimates of α_i and β_i in Eq. (1) from regressing $\{r_t\}_{t=2}^{R}$ on a constant and $\{z_{i,t}\}_{t=1}^{R-1}$. The next out-of-sample forecast is obtained as

$$\hat{r}_{R+2} = \hat{\alpha}_{R+1,i} + \hat{\beta}_{R+1,i} z_{R+1,i}, \quad (5)$$

where $\hat{\alpha}_{R+1,i}$ and $\hat{\beta}_{R+1,i}$ are the OLS estimates of α_i and β_i in Eq. (1) from regressing $\{r_t\}_{t=2}^{R+1}$ on a constant and $\{z_{i,t}\}_{t=1}^{R}$. Continuing to construct the out-of-sample forecasts in this manner, a series of Q out-of-sample forecasts for the equity risk premium can be generated as $\{\hat{r}_t\}_{t=R+1}^{T}$. For the initial in-sample portion of the sample, this study chooses $R = \frac{1}{3}T$.

The out-of-sample forecasts based on the dynamic factor model in (3) can be obtained as:

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \sum_{k=1}^{K} \hat{\beta}_{t,k} \hat{f}_{k,t}, \quad (6)$$

where $\hat{f}_{k,t}$ is the k-th diffusion index extracted from the 12 financial and macroeconomic variables based on the data through t, and $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,k}$ are the OLS estimates from the Eq. (3). Following the same procedure as in the univariate predictive regressions, a series of Q out-of-sample forecasts for the equity risk premium can be generated.

In order to evaluate the out-of-sample predictability of individual variables and diffusion indexes, the study chooses the popular benchmark forecast proposed by Goyal and Welch (2003) and Welch and Goyal (2008), which is the historical average forecast of stock returns, $\hat{r}_{t+1}^{HA} = \frac{1}{t}\sum_{s=1}^{t} r_s$. It is an equity risk premium forecast when we assume a constant expected equity risk premium and a very stringent out-of-sample benchmark.

For the forecast evaluation, this study adopts the out-of-sample R^2 statistic, R_{OS}^2, proposed by Campbell and Thompson (2008) and the MSFE-adjusted statistic proposed by Clark and West (2007). First of all, the mean squared forecast error (MSFE) for the predictive regression forecast over the forecast evaluation period, Q, is given by $MSFE_i = \frac{1}{Q}\sum_{s=1}^{Q}\left(r_{R+s} - \hat{r}_{i,R+s}\right)^2$, where $\hat{r}_{i,R+s}$ denotes the equity risk premium forecast by individual predictor or diffusion indexes. Letting $MSFE_0 = \frac{1}{Q}\sum_{s=1}^{Q}\left(r_{R+s} - \hat{r}_{R+s}^{HA}\right)^2$, the R_{OS}^2 for the equity risk premium forecast is given by $R_{i,OS}^2 =$

$1-\left(\frac{MSFE_1}{MSFE_0}\right)$ for the given predictive regression. A positive R^2_{OS}-value indicates that the predictive regression forecast outperforms the historical average in terms of the MSFE, while a negative value suggests the opposite.

The MSFE-adjusted statistic can be computed by first defining

$$f_{i,t+1}=\left(r_{t+1}-\hat{r}^{HA}_{t+1}\right)^2-\left[\left(r_{t+1}-\hat{r}_{i,t+1}\right)^2-\left(\hat{r}^{HA}_{t+1}-\hat{r}_{i,t+1}\right)^2\right], \quad (7)$$

and regressing $\{f_{i,s+1}\}_{s=R}^{T-1}$ on a constant. The resulting *t*-statistic corresponding to this regression tests the null hypothesis that the historical average MSFE is less than or equal to the predictive regression MSFE against the one-sided (upper-tail) alternative hypothesis that the historical average MSFE is greater than the predictive regression MSFE.

IV. Results and Discussions

A. Empirical results of in-sample and out-of-sample predictability

Table 2 presents the estimation results of in-sample predictive regressions using both the individual predictive variables and the dynamic factor model. The table reports the slope coefficient estimates of β_i in Eq. (1) and (3), along with the heteroskedasticity-consistent *t*-statistics and the R^2 statistics. In order to test the null hypothesis of no predictability, the one-sided upper-tail wild bootstrapped *p*-values are also provided for the t-statistics.

Panel A of Table 2 reports the regression results for individual financial and macroeconomic variables. There are four of the 12 variables that exhibit significant predictive power at the 5% level for the future equity risk premium of the KOSPI: dividend-price ratio, dividend yield, book-to-market ratio, and term spread. The R^2 statistics for these variables are about 2-3 percent,

Table 2. In-sample Predictive Regression Results, October 2000 to December 2020

Predictor	Slope Coefficient	*t*-statistic	*p*-value	R^2(%)	*Adj*-R^2(%)
Panel A. Univariate Predictive Regressions					
DPR	3.382	2.245**	0.024	2.009	1.599
DYR	3.661	2.327**	0.025	2.426	2.018
EPR	1.000	0.667	0.305	0.280	- 0.137
BMR	5.479	2.197**	0.029	2.709	2.301
STR	0.313	0.950	0.177	0.578	0.162
LTR	0.049	0.184	0.456	0.019	- 0.400
TMS	0.923	1.721**	0.039	1.351	0.939
DFS	0.184	0.550	0.304	0.154	- 0.264
CRS	0.758	0.853	0.235	0.498	0.081
IFL	0.630	0.544	0.311	0.154	- 0.263
IPG	- 0.012	- 0.041	0.507	0.001	- 0.418
SVR	52.382	0.640	0.303	0.268	- 0.150
Panel B. Dynamic Factor Model					
DI-1	-0.153	- 0.647	0.720	3.544	2.323
DI-2	0.552	2.241**	0.021		
DI-3	0.491	1.508	0.109		

Notes. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The column with *p*-values reports the one-sided upper-tail wild bootstrapped *p*-values for the *t*-statistics. The R^2 statistics and the adjusted R^2 statistics reported in the fifth and sixth columns are computed for the full sample.

which appear small. However, they may represent an economically significant degree of predictability since Campbell and Thompson (2008) points out that a monthly R^2 of more than 0.5% indicate an economically meaningful predictability.

Turning to the regression results using the dynamic factor model, Panel B of Table 2 provides the slope coefficient estimates with the *t*-statistics for three diffusion indexes. The coefficient estimate for the second diffusion index is significant at the 5% level. The R^2 and the adjusted R^2 statistics for the dynamic factor predictive model are 3.544% and 2.323%, which are greater than not only the 0.5% benchmark but any other R^2 or adjusted-R^2 value for the univariate regression. Therefore, the regression results show that even though not every diffusion index exhibits statistically significant predictability, the dynamic factor predictive regression model can improve the degree of future equity risk premium predictability upon the individual predictive regression models.

Table 3 presents the results for out-of-sample tests of equity risk premium predictability for the univariate predictive regressions and the dynamic factor predictive regression model. In Panel A reporting the univariate predictive regression forecasts, only two variables of boot-to-market ratio and term spread have the positive R^2_{OS}, which indicates the predictive regressions employing these variables outperform the benchmark historical average of the equity risk premiums in terms of the MSFE. In other words, most of the twelve financial and macroeconomic variables fail to outperform the simple historical average in predicting the future equity risk premiums. Evaluating their out-of-sample predictive power with the more formal test statistics, the MSFE-adjusted statistics, indicates that the MSFE for the book-to-market ratio is significantly less than the historical average MSFE at the 5% level while the difference of the MSFE for the term spread from the historical average MSFE is significant at the 10% level. This results confirms the findings by Chun (2020) and Chun

Table 3. Out-of-sample Forecasting Evaluation

Predictor	MSFE	R^2_{OS}(%)	MSFE-adjusted	*p*-value
Panel A. Historical Averages				
HA	28.608			
Panel B. Univariate Predictive Regressions				
DPR	29.416	-2.824	1.059	0.145
DYR	29.650	-3.643	1.128	0.130
EPR	29.482	-3.053	-0.964	0.833
BMR	27.678	3.251	1.988**	0.023
STR	28.902	-1.026	1.314*	0.094
LTR	29.074	-1.628	-0.572	0.716
TMS	28.411	0.690	1.288*	0.099
DFS	29.212	-2.111	0.599	0.275
CRS	29.229	-2.169	-0.656	0.744
IFL	29.010	-1.406	-0.821	0.794
IPG	29.204	-2.084	-2.293	0.989
SVR	29.037	-1.498	-0.840	0.800
Panel C. Dynamic Factor Model				
DI-Model	27.837	2.694	1.827**	0.034

Notes. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. MSFE is the mean squared forecast error and R^2_{OS} measures the proportional reduction in the MSFE for the given forecast model with respect to the MSFE for the historical average forecast. MSFE-adjusted is the Clark and West (2007) statistic to test the null hypothesis that the MSFE for the historical average forecast less than or equal to the MSFE for the given forecast model. The column with *p*-values reports the one-sided upper-tail wild bootstrapped *p*-values for the MSFE-adjusted statistics.

(2021) that the book-to-market ratio has a significant predictive power in the Korean stock market in recent data. It is also interesting to see that the MSFE-adjusted statistic for short-term interest rate is significant at the 10% level even though its R^2_{OS} is negative, which can happen when comparing nested model forecasts as suggested by Clark and West (2007).

Panel B of Table 3 presents the out-of-sample test results of the dynamic factor predictive regression forecasts based on the financial and macroeconomic variables. The R^2_{OS} is positive and the second largest next to the R^2_{OS} value of the book-to-market ratio. Also, the MSFE-adjusted statistic indicates that its MSFE is significantly less than the historical average MSFE at the 5% level. Therefore, it can be concluded that the dynamic factor predictive regression forecast reveals significant out-of-sample predictability in the Korean stock market, as strong as that of book-to-market ratio.

B. Discussions of economic implications for the diffusion indexes

In this section, Figure 1 presents the estimated latent factors and factor loadings using the Eq. (2) to provide economic implications of the diffusion indexes. In the figure, panels A, C, and E show the time series of the diffusion indexes and panels B,

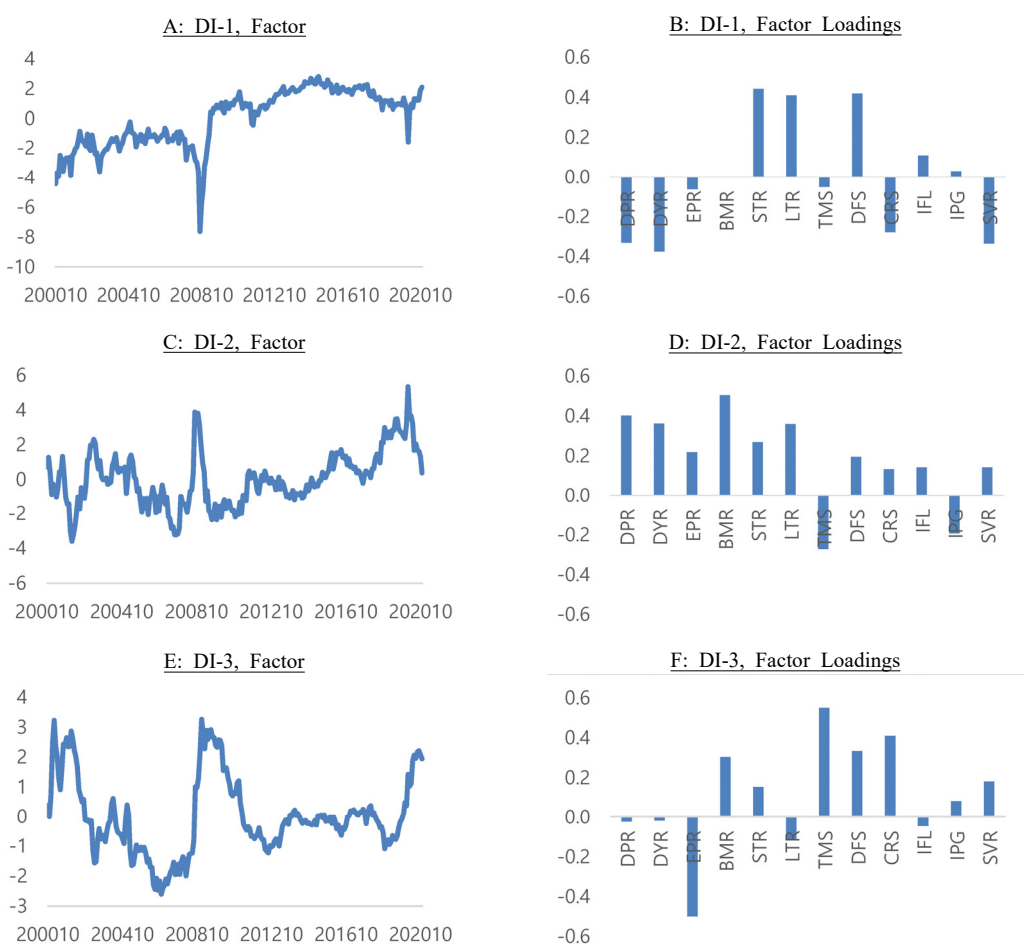

Figure 1. Estimates of Factors and Factor Loadings using 12 Predictive Variables

D, and F show the factor loadings for the individual predictive variables on the diffusion indexes. Firstly, panel B indicates that the first factor, DI-1, is primarily loaded with the macroeconomic variables such as short-term and long-term interest rates and default-spread. As a result, the DI-1 series in panel A suffers from large drops during the global financial crisis in 2008 or the recent COVID-19 event. The second factor, DI-2, in panel D is relatively strongly loaded with both the valuation ratios like DPR, DYR, EPR and BMR, and the macroeconomic variables like STR and LTR. The DI-2 series exhibits substantial fluctuations in panel C. Note that the DI-2 has a significant slope coefficient estimate for predictive regression in Table 2 and it may be due to the fact that it reflects various different financial and macroeconomic variables and thus captures more useful predictive information. The third factor, DI-3, is mainly loaded with interest spreads such as TMS, DFS, and CRS, and the DI-3 series tend to move opposite to the DI-1 factor in panel E. The autocorrelations for DI-1, DI-2, and DI-3 are 0.96, 0.92, 0.96, respectively. The relatively lower autocorrelation of DI-2 indicates that this factor is less likely to suffer from finite-sample bias and it is more likely to deliver better forecasts of the equity risk premium than other factors.

V. Conclusions

In this article, the dynamic factor model is adopted to directly predict the future equity risk premium in the Korean stock market and its predictive power is compared to that of univariate regression models employing various individual financial and macroeconomic variables. The in-sample test results show that the dynamic factor predictive regression model delivers statistically and economically significant predictive power for the future equity risk premium, as strongly as the best individual predictor can do. The out-of-sample test results reaffirms the model's in-sample predictive power in that the dynamic factor predictive model outperforms the benchmark historical average in both the R^2_{OS} and the MSFE-adjusted statistics. Through the detailed analysis of the diffusion indexes, it is found that each factor captures different information from various financial and macroeconomic variables relevant for return prediction and the predictive regression model employing diffusion indexes can deliver better forecasts of the future equity risk premium.

Even though the empirical results imply significant improvements in the Korean stock market return predictability by adopting the dynamic factor model, there exist also some potential limitations of the study. Firstly, the in-sample and out-of-sample predictability of the model is evaluated based on the sample periods from 2000 to 2020, which also include the global financial crisis. As suggested by Baltas and Karyampas (2018), the forecasting ability of the predictive models can be regime-dependent and if the models generate substantially large forecast errors during market downturns, the asset allocation strategy depending on these models may give rise to significant relative losses. Therefore, the predictive power of the dynamic factor model may further need to be evaluated under different business conditions. Secondly, this paper utilizes the macroeconomic and financial information to predict the future equity risk premiums but expanding the dataset to include the technical indicators or the information in newspapers may further improve the predictive power of the dynamic factor model. Neely et al. (2014) demonstrate that technical indicators better detect the decline in the equity risk premium near business-cycle peaks and combining information from both technical indicators and macroeconomic variables significantly improves the equity risk premium forecasts for the U.S. stock market. Adämmer and Schüssler (2020) suggest that the information embedded in the extracted news is not captured by the macroeconomic variables and the equity risk premium forecasts based on extracted news exhibit forecasting gains, particularly in market downturns. The investigation of these issues is left for future research.

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