Stock Returns Predictable:
Some New Evidence from the Korean Stock Market

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ABSTRACT

This paper makes three contributions to the literature on predictability stock returns in the Korean stock market. We focus on out-of-sample forecasting of returns based on industry portfolios are predictability. From the results, we discover that in-sample and out-of-sample test during from 2000 to 2015, predictability is not homogeneous. Furthermore, we examine the determinants of out-of-sample predictability for each sector using industry characteristics and find strong evidence that return predictability has links to certain industry characteristics, such as book-to-market ratio, dividend yield, size, price earnings ratio, and trading volume. We also discover a mean combination forecast approach which has significant out-of-sample performance.

Keywords: Stock returns, Predictability, Korean stock market

1. Introduction

The debate about whether the stock returns can be predicted has always been a hot arguable issue in the financial studies of asset pricing. Several empirical studies show that financial ratios and macro variables, such as dividend-price, price earnings, dividend pay-out, and book to market ratios, inflation rate, interest rates, aggregate output predict stock returns (Westerlund and Narayan, 2012, 2014; Narayan, Bannigidadmath, 2015). So, there is no surprising that stock returns are predictable

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using macro variables. However, the empirical evidence is far from univocal in providing support for stock return predictability using macro variables. Some studies find that the predictive ability of certain macro variables with respect to equity returns is quite uneven over time (Rapacha, et al. 2005).

However, there is still limited evidence of predictability using out-of-sample tests (Butler et al., 2005; and Ang and Bekaert, 2007). For instance, Welch and Goyal (2008) find that the out-of-sample stock return forecast fails to beat the simple historical average benchmark forecast. They also test the predictive power of the predictors by including all predictors in a single model and they concluded that the predictive regression models were not stable and were unable to beat the historical average. On the other hand, Rapach et al. (2010) showed that the combination predictive regression, which included 15 economic variables, could beat the historical average model in out-of-sample forecasting of the stock returns in different sample periods.

In this paper, we re-examine to take an extensive empirical investigation of stock return predictability for Korea. In order to see the practical aspect of stock return predictability, we form three sets of component portfolios: industry portfolios, portfolios sorted on book-to-market, portfolios sorted on market capitalization (size) within the aggregate market return portfolio. First of all, we based on a wide range of portfolios sorted by firm characteristics and industry classifications to test for return predictability. Second, we consider both in-sample and outof-sample tests of return predictability in the present paper by Westerlund and Narayan (2012, 2014) and we also employ a wide range of evaluation metrics to judge out of sample forecasting performance. Third, having ascertained statistical evidence of predictability, we explore economic explanations for this predictability.

Our in-sample analysis employs a predictive regression framework, with samples typically beginning in the early 2000 and ending in the late 2015. For our out-of-sample analysis, we reserve a period covering the bull market of the early 2000s over which we analyze out-of-sample forecasts of returns. In-sample results reveal that economic variables, such as book-to-market (BM) ratio, dividend-price (DP) ratio, dividend yield (DY), dividend payout (DE) ratio, and earnings-price (EP) ratio predict aggregate market excess returns. At the industry-level, DE, EP and DP predict returns consistently. Stock variance (SVAR) has very limited content to predict returns of aggregate market and its components. By comparison while the out-of-sample tests also reveal similar evidence of return predictability, the role of predictors is different from those found when using the in-sample tests.

Second, given the differences in predictability using individual predictors, we compute out-of-sample forecasts based on a mean combination forecast approach proposed by Rapach et al. (2010). The main advantage of this approach is that because it simply takes the average of forecasts obtained using each predictor, it incorporates more information while reducing forecast volatility. We find that the combination forecasts pick up economically meaningful changes in all the seven economic variables and significantly improve the out-of-sample forecasting performance relative to individual predictive regression models. Third, we attempt to provide economic explanations for differences in return predictability across the components.

The balance of the paper progresses as follows. In Section 2, we discuss the in-sample predictability test. Section 3 is about the out-of-sample forecasting evaluations. Economic explanations for predictability are provided in Section 4. The final section provides some concluding remarks.

2. Methodology

2.1. In-sample predictability tests

We examine in-sample evidence of stock return predictability. We begin with the WN test, for which we report the 95% confidence interval for β based on both the asymptotic FQGLS *t*-test as well as the sub-sample FQGLS *t*-test. We give greater weight to results based on the sub-sample test for the reason that it works best when the predictor variable is persistent, as shown in the Monte Carlo simulations conducted and reported in Westerlund and Narayan (2014). The interpretation is simple; when the confidence interval includes the value zero, we cannot reject the null hypothesis of no predictability.

In-sample predictability test results for the aggregate market and industry portfolio excess returns. This table reports the in-sample predictability test results for the aggregate market and ten industries based on the following regression model:

$$r_t = \alpha + \beta x_{t-1} + \varepsilon_{r,t}$$

Here, r_t is excess return for the aggregate market or the industry portfolio, and x_t is the predictor variable, which takes the form of one of the seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), and stock variance (SVAR). We employ the following Westerlund and Narayan (2012, 2014) FQGLS-based *t*-statistic for testing β = 0:

$$t_{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \pi_t^2 x_{t-1}^d r_t^d}{\sqrt{\sum_{t=q_m+2}^{T} \pi_t^2 (x_{t-1}^d)^2}}$$

where π_t = $1/\sigma_{\eta t}$ is the FQGLS weight, and $x_t^d = x_t - \sum_{s=2}^{T} x_s/T$ with a similar definition of r_t^d, where T is the sample size, and q = max{q_x, $q_{r,x}$}. We report the 95% confidence interval for β based on both the sub-sample FQGLS test ($t_{\text{FQGLS}}^{\text{sub}}$) and the asymptotic FQGLS test (t_{FQGLS}). The estimation covers the sample period 2000–2015. When the confidence interval includes the value zero, we cannot reject the null of no predictability.

2.2. Out-of-sample forecast evaluation measures

We examine the out-of-sample forecasting performance using a recursive window approach, following Rapach et al. (2010) and Narayan et al. (2013). We estimate the predictive regression model for the in-sample period t_0 to t and forecast the returns for the period t + 1. We then re-estimate the model over the period t_0 to t + 1 and forecast the returns for the eriod t + 2. This process continues until all the data are exhausted. Since we are undertaking recursive forecasting, we are taking into account the information available up to the previous day, thereby mimicking real-time forecasting. The out-of-sample period is set to 20% of the full-sample of data. The out-of-sample estimation covers the period 2010:07 to 2015:06.

We use six well-known measures to evaluate the accuracy of the forecasts. The relative mean absolute error (RMAE) is given by:

$$\text{RMAE} = \text{MAEM} - \text{MAEH}$$

where MAE_M and MAE_H are the mean absolute errors for the predictive regression model and the historical mean model, respectively. The relative root mean squared error (RRMSE) is given by:

$$\text{RRMSE} = \text{RMSEM}/\text{RMSEH}$$

where RMSE_M and RMSE_H are the root mean squared errors for the predictive regression model and the historical mean model, respectively. We employ the Campbell and Thompson (2008) out-of-sample R^2 (OR^2) for comparing mean square forecast errors:

$$OR^2 = 1 - (\text{MSFE}_M/\text{MSFE}_H)$$

Here, MSFE_M and MSFE_H are the mean squared forecast errors for the predictive regression model and the historical average model, respectively. We also compute the Clark and West (2007) MSFE - adjusted test statistic, which examines the null hypothesis that $OR^2 \leq 0$ against the alternative hypothesis $OR^2 > 0$. The other two forecast evaluation metrics used are the Mincer–Zarnowitz R^2 and the success ratio. The Mincer–Zarnowitz R^2 (RMZ) is the R^2 from the following time-series least squares regression model:

$$r_t = c + d\hat{r}_t + \varepsilon_t$$

where r_t and $\hat{r_t}$ are the actual and forecasted returns, respectively. The success ratio (SR) is the percentage of times the sign of forecasted returns is the same as the sign of the actual returns. To compare the predictive regression model forecasts with the historical average forecasts, we use the relative success ratio (RSR), which is computed as the success ratio for our proposed model divided by the success ratio of the benchmark historical mean model. When RSR is greater than one, it indicates that our proposed model predicts the sign of returns accurately relative to the historical mean model.

2.3. Data

We use a monthly data set obtained from FnGuide to examine return predictability for the Korean aggregate market portfolio. To ensure that we have a reasonable number of firm-level observations, the sample period after computation of all the financial ratios and portfolio returns begins in July 2000 and ends in June 2015.

We confirm their effective ending months according to two criterions: (i) consecutive constant closing price records (P) from the month until the end of the period, June 2015; and, (ii) zero trading volume (VO) from the month until the end of the period. A stock with same month as its starting month and ending month is excluded from the sample. Any stock return above 300% that is reversed within one month is set to missing. Specifically, if ret_t or ret_{t-1} is greater than 300%, and if $(1 + ret_t) * (1 + ret_{t-1}) - 1 \leq 50\%$, then both ret_t and ret_{t-1} are set to missing. Additionally, we treat as missing the monthly returns that fall out of the 0.1% and 99.9% percentile ranges. We also exclude stocks with less than 12 monthly returns from our sample.

Lastly, the included firms are required to have at least one firm-year observation for five financial variables - market value of equity, book value per share, dividends per share, and earnings per share.

The aggregate market portfolio is the value-weighted return of all the stocks in our sample. For the industry portfolios, we use the FnGuide variable to classify the firms into seven industries as per the Korean Industry Classification Benchmark. The industry portfolio returns are computed as value-weighted returns of all the stocks in each industry.

Table 1

This table lists the variable names and descriptions for all the variables downloaded from FnGuide.

Predictor name	Description
Book-to-market ratio (BM)	For the months of July of year t to June of year t + 1, BM is computed by dividing the book value for fiscal year-end in year t – 1 by the price (P) at the end of the current month
Dividend payout ratio (DE)	It is the difference between the log dividends and log earnings. The dividends and earnings for fiscal year-end in year t - 1 are used to compute DE for the months of July of year t to June of year t + 1
Dividend-price ratio(DP)	It is the difference between the log dividends and log of stock prices (P). For the months of July of year

	t to June of year t + 1, DP is computed by dividing the log dividends for fiscal year-end in year t - 1 by the log price at the end of the current month
Dividend yield (DY)	It is the difference between the log dividends and log of one-period lagged stock price (P). DY for the months of July of year t to June of year t + 1 is computed by dividing the log dividends for fiscal year-end in year t - 1 by the log of one-period lagged stock price
Earnings-price ratio (EP)	It is the difference between the log earnings and log of stock prices (P). For the months of July of year t to June of year t + 1, EP is computed by dividing the log earnings for fiscal year-end in year t - 1 by the log price at the end of the current month
Inflation (INF)	It is computed using the consumer price index data downloaded from the FnGuide financial database
Stock variance (SVAR)	It is the sum of squared daily returns on the value-weighted KOSPI index return

3. Empirical result

3.1. Preliminary statistical features of the data

The Table 2 reports the summary statistics for excess returns for the aggregate market portfolio and its component portfolios that include the seven economic variables, for the period 2000:07–2015:06.

Table 2

This table reports sample means and standard deviations in percentage for excess returns and the seven economic variables covering the sample period 2000:07 to 2015:06. The excess returns are the returns in excess of weighted average call money rate for Korea. Skewness and kurtosis are also reported for all the portfolios. Panel A reports the summary statistics for the value-weighted aggregate market portfolio (Market) and the seven value-weighted industry portfolios. Panel B reports the summary statistics for seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), and stock variance (SVAR) used as predictors of returns.

	Mean	SD	Median	Max	Min	Skew	Kurt
Panel A: Aggregate market and industry portfolio excess returns							
Market	-3.757	7.147	-2.732	14.204	-31.971	-0.794	1.517
Construction	-4.675	9.1274	-4.040	18.035	-32.449	-0.251	0.258
Distribution	-4.489	6.935	-4.254	13.211	-32.116	-0.719	1.506
Financials	-4.134	8.641	-3.408	18.401	-33.202	-0.365	0.909
Manufacturing	-4.038	6.637	-3.434	13.413	-31.840	-0.656	1.272
Service	-3.689	6.912	-3.049	13.454	-31.939	-0.685	1.071
Transportation & Commucation	-4.324	7.640	-3.461	12.899	-28.175	-0.466	0.626
Utilities	-3.641	5.948	-3.395	11.133	-30.361	-0.820	2.860
Panel B: Economics variables							
BM	2.004	0.569	1.767	2.902	1.049	0.251	-1.255
DE	-1.448	0.180	-1.380	-1.201	-1.764	-0.520	-1.217
DP	-4.427	0.280	-4.496	-4.019	-4.813	0.010	-1.555
DY	-4.425	0.257	-4.403	-3.969	-4.775	0.049	-1.380
EP	-1.448	0.180	-1.380	-1.201	-1.764	-0.520	-1.217
INF	0.002	0.004	0.002	0.013	-0.006	0.208	-0.053
SVAR	0.005	0.007	0.003	0.063	0.000	4.081	26.684

Panel A shows that average monthly industry excess returns range from -4.675% for Construction to -3.641% for Utilities sector with standard deviations of 5.948% and 9.126%, respectively. The main implication of these descriptive statistics is that the market, its industry components, are heterogeneous. The resulting question addressed in the remaining sections is: Are predictability and profitability also heterogeneous?

Our main objective in this section is to gauge to what extent our predictive regression model is characterized by persistent and endogenous predictors and, to what extent, if at all, our model suffers from heteroskedasticity. We begin with a test of the null hypothesis of a unit root in variables relating to the market and each of the seven industries in our sample. The results are reported in Table 3.

Table 3

ADF unit root test results for the aggregate market and industry portfolios. This table reports the augmented Dickey and Fuller (1981) unit root test results for the excess returns and for each of the seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), and stock variance (SVAR) used as predictors of returns. The results are reported for the aggregate market and each of the ten industries. The unit root test results are based on the ADF model and are implemented by including only the intercept term. We use the Schwarz information criterion and set a maximum of eight lags to obtain the optimal lag length. The test statistics and the resulting p-values are reported for each of the variables.

	Test stat	*p*-Value	Test stat	*p*-Value	Test stat	*p*-Value
	Returns		BM		DE	
Market	-11.865	0.000	-2.294	0.175	-0.099	0.947
Construction	-11.555	0.000	-1.570	0.496	-1.062	0.731
Distribution	-11.600	0.000	-2.329	0.164	-0.218	0.933
Financials	-11.643	0.000	-2.955	0.041	-0.568	0.874
Manufacturing	-11.314	0.000	-1.661	0.450	-0.093	0.948
Service	-10.748	0.000	-2.698	0.076	-0.202	0.935
Transportation & Commucation	-12.132	0.000	-2.103	0.244	-0.775	0.823
Utilities	-12.016	0.000	-1.804	0.378	-0.435	0.899
	DY		EP		DP	
Market	-1.208	0.671	-0.099	0.947	-1.008	0.750
Construction	-2.304	0.172	-1.673	0.443	-1.748	0.405
Distribution	-1.334	0.613	-2.361	0.154	-0.834	0.807
Financials	-1.622	0.469	-1.445	0.559	-1.294	0.632
Manufacturing	-1.044	0.737	-2.238	0.194	-0.806	0.815
Service	-1.803	0.378	-2.499	0.117	-0.773	0.824
Transportation & Commucation	-1.876	0.343	-2.728	0.071	-2.273	0.182
Utilities	-2.726	0.071	-1.999	0.287	-0.957	0.768
	INF		SVAR			
	-11.443	0.000	-7.167	0.000		

The unit root test is based on the familiar augmented Dickey and Fuller (1981) time-series regression model and is implemented by including only the intercept term. We use the Schwarz information criterion and a maximum of eight lags to obtain the optimal lag length. The test statistic, together with its *p*-value, is reported for each of the variables. The optimal lag length is reported in square brackets. The unit root null is rejected for returns of the market and for each of the seven industries, rendering returns, as expected, to be strongly stationary. When we consider the economic variables predicting the aggregate market portfolio, the unit root null is rejected for seven variables at the 1% significance level;

For all of the seven industries, for economic variable EP, DE, DP and DY the unit root null is rejected for seven industries; while, for variables BM, the unit root null is rejected for six of seven industries. This indicates mixed evidence of integration of predictor variables at the industry-level.

However, since the rejection of the unit root null does not imply that the variables are not persistent, we report in Table 4 the AR(1) coefficient for each of the variables.

Table 4

Results for the first-order autoregressive coefficient. This table reports the degree of persistency in excess returns and the seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), and stock variance (SVAR) used as predictor of returns. The estimate is based on an autoregressive model of order one. The results are reported for the aggregate market and the ten industries.

	Returns	BM	DE	DP	DY	EP	INF	SVAR
Market	0.156	0.946	0.999	0.989	0.981	0.989	0.284	0.579
Construction	0.175	0.976	0.987	0.967	0.950	0.970		
Distribution	0.171	0.949	0.998	0.992	0.979	0.943		
Financials	0.165	0.912	0.995	0.971	0.972	0.913		
Manufacturing	0.196	0.968	0.999	0.992	0.984	0.962		
Service	0.251	0.944	0.998	0.988	0.965	0.953		
Transportation & Commucation	0.133	0.965	0.992	0.958	0.963	0.934		
Utilities	0.158	0.967	0.996	0.984	0.947	0.969		

What we notice immediately is that for all the predictors, except SVAR, the coefficient is close to one. This is a sign that most of the variables are highly persistent. In Table 5, we report the results for autocorrelations associated with the square of each variable.

Table 5

Results for heteroskedasticity tests for the aggregate market and industry portfolios. This table reports the heteroskedasticity test results for excess returns and the seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), and stock variance (SVAR) used as predictors of returns. The results are reported for the aggregate market and for each of the ten industries. We square the variables and estimate the autocorrelations associated with the squared variables. The Q-statistics at lags 1, 4, 8 and 12 are reported with p-values in parenthesis.

	Lag 1		Lag 4		Lag 8		Lag 12	
				Returns				
Market	4.739	0.029	16.473	0.002	17.192	0.028	18.337	0.106
Construction	5.966	0.015	11.557	0.021	13.764	0.088	18.794	0.094
Distribution	5.732	0.017	12.041	0.017	13.532	0.095	22.038	0.037
Financials	5.291	0.021	12.822	0.012	13.608	0.093	14.877	0.248
Manufacturing	7.506	0.006	15.362	0.004	16.248	0.039	21.401	0.045
Service	12.271	0.000	22.994	0.000	24.307	0.002	29.225	0.004
Transportation & Commucation	3.435	0.064	12.472	0.014	17.335	0.027	21.528	0.043
Utilities	4.846	0.028	12.769	0.012	18.786	0.016	25.735	0.012

				BM				
Market	173.580	0.000	582.250	0.000	909.590	0.000	1062.400	0.000
Construction	184.530	0.000	683.230	0.000	1232.200	0.000	1676.600	0.000
Distribution	174.230	0.000	588.060	0.000	931.470	0.000	1117.600	0.000
Financials	161.970	0.000	483.400	0.000	635.140	0.000	647.060	0.000
Manufacturing	179.570	0.000	636.640	0.000	1076.400	0.000	1359.100	0.000
Service	173.180	0.000	578.720	0.000	903.260	0.000	1067.200	0.000
Transportation & Commucation	180.770	0.000	647.730	0.000	1110.200	0.000	1415.300	0.000
Utilities	182.190	0.000	661.080	0.000	1154.000	0.000	1500.700	0.000

Table 5 (*continue*d)

				DE				
Market	189.980	0.000	736.080	0.000	1404.800	0.000	1990.200	0.000
Construction	188.410	0.000	720.620	0.000	1351.200	0.000	1879.900	0.000
Distribution	190.860	0.000	744.720	0.000	1434.300	0.000	2048.000	0.000
Financials	188.080	0.000	717.430	0.000	1337.900	0.000	1842.500	0.000
Manufacturing	189.750	0.000	733.740	0.000	1397.400	0.000	1978.600	0.000
Service	189.890	0.000	735.140	0.000	1401.800	0.000	1985.400	0.000
Transportation & Commucation	186.980	0.000	706.770	0.000	1309.400	0.000	1821.100	0.000
Utilities	186.110	0.000	698.360	0.000	1286.200	0.000	1799.400	0.000
				DP				
Market	186.830	0.000	705.350	0.000	1301.900	0.000	1793.500	0.000
Construction	181.320	0.000	652.940	0.000	1128.100	0.000	1453.800	0.000
Distribution	188.540	0.000	721.950	0.000	1359.200	0.000	1912.200	0.000
Financials	182.530	0.000	664.290	0.000	1161.100	0.000	1500.300	0.000
Manufacturing	187.340	0.000	710.260	0.000	1319.100	0.000	1830.500	0.000
Service	186.120	0.000	698.510	0.000	1278.900	0.000	1748.200	0.000
Transportation & Commucation	178.100	0.000	623.080	0.000	1034.500	0.000	1284.700	0.000
Utilities	181.730	0.000	656.740	0.000	1147.700	0.000	1523.200	0.000
				DY				
Market	184.060	0.000	678.780	0.000	1217.500	0.000	1648.300	0.000
Construction	174.180	0.000	587.630	0.000	940.160	0.000	1174.600	0.000
Distribution	184.170	0.000	679.830	0.000	1212.100	0.000	1598.000	0.000
Financials	182.760	0.000	666.430	0.000	1165.300	0.000	1496.100	0.000
Manufacturing	184.490	0.000	682.840	0.000	1230.700	0.000	1672.500	0.000
Service	178.210	0.000	624.090	0.000	1050.700	0.000	1371.700	0.000
Transportation & Commucation	179.750	0.000	638.270	0.000	1077.300	0.000	1342.800	0.000
Utilities	172.330	0.000	571.230	0.000	905.030	0.000	1174.200	0.000
				EP				
Market	189.980	0.000	736.080	0.000	1404.800	0.000	1990.200	0.000
Construction	182.370	0.000	662.780	0.000	1157.600	0.000	1499.400	0.000
Distribution	173.330	0.000	580.010	0.000	899.730	0.000	1034.100	0.000
Financials	161.410	0.000	478.810	0.000	624.330	0.000	635.150	0.000
Manufacturing	178.600	0.000	627.670	0.000	1053.500	0.000	1339.200	0.000
Service	175.850	0.000	602.630	0.000	980.070	0.000	1222.800	0.000
Transportation & Commucation	169.460	0.000	546.210	0.000	802.650	0.000	878.860	0.000
Utilities	182.610	0.000	665.030	0.000	1168.300	0.000	1534.300	0.000
				INF				
Market	15.707	0.000	41.926	0.000	65.047	0.000	125.740	0.000
				SVAR				
Market	65.118	0.000	138.810	0.000	176.360	0.000	195.200	0.000

We notice that while for all the predictors, the autocorrelations are significant, for returns the p-values tend to increase with more distant lags. Presence of ARCH can be implied from autocorrelation in squared variables. This evidence suggests strong ARCH effects in both the predictors and the returns.

We undertake further tests of ARCH effects by filtering each series and running an autoregressive regression model with twelve lags. We then apply the Lagrange Multiplier test to examine the null hypothesis of ‘no ARCH’ in the filtered series. The results are presented in Table 6.

Table 6

Results for ARCH effects for the aggregate market and industry portfolios. This table reports the ARCH test results for excess returns and the seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), and stock variance (SVAR) used as predictors of returns. The results are reported for the aggregate market and for each of the ten industries. We undertake ARCH tests by filtering each series through running an autoregressive regression model with twelve lags. We then apply the Lagrange Multiplier test to examine the null hypothesis of no ARCH in the filtered series. The F-statistics at lags 1, 4, 6 and 12 are reported with resulting p-values in the second column.

	ARCH (1)		ARCH (4)		ARCH (6)		ARCH (12)	
				Returns				
Market	6.751	0.010	3.181	0.015	2.345	0.033	1.222	0.271
Construction	0.642	0.424	2.510	0.043	1.958	0.074	1.585	0.099
Distribution	3.380	0.068	1.136	0.341	0.881	0.510	1.125	0.343
Financials	1.672	0.198	3.061	0.018	2.086	0.057	1.236	0.262
Manufacturing	2.341	0.128	1.092	0.362	0.998	0.429	0.876	0.573
Service	0.989	0.321	0.602	0.661	0.738	0.620	0.718	0.733
Transportation & Commucation	1.846	0.176	1.633	0.168	1.417	0.210	1.073	0.385
Utilities	7.164	0.008	2.396	0.052	2.086	0.057	1.521	0.120
				BM				
Market	0.142	0.707	0.151	0.963	0.163	0.986	2.288	0.010
Construction	0.013	0.911	0.012	1.000	0.013	1.000	0.715	0.718
Distribution	0.080	0.778	0.076	0.990	0.083	0.998	2.515	0.004
Financials	0.402	0.527	0.462	0.763	0.515	0.797	4.576	0.000
Manufacturing	0.055	0.816	0.058	0.994	0.059	0.999	9.211	0.000
Service	0.048	0.826	0.036	0.998	0.034	1.000	3.878	0.000
Transportation & Commucation	0.012	0.912	0.009	1.000	0.008	1.000	4.065	0.000
Utilities	0.048	0.826	0.049	0.995	0.049	1.000	0.405	0.960
				DE				
Market	0.022	0.884	0.023	0.999	0.029	1.000	0.209	0.998
Construction	0.009	0.925	0.009	1.000	0.009	1.000	2.813	0.002
Distribution	0.020	0.886	0.022	0.999	0.030	1.000	0.608	0.834
Financials	0.009	0.924	0.010	1.000	0.014	1.000	1.004	0.447
Manufacturing	0.014	0.904	0.016	1.000	0.020	1.000	0.214	0.998
Service	0.007	0.935	0.007	1.000	0.010	1.000	0.252	0.995
Transportation & Commucation	0.003	0.956	0.003	1.000	0.003	1.000	0.540	0.886
Utilities	0.027	0.870	0.030	0.998	0.028	1.000	0.161	0.999
				DP				
Market	0.001	0.971	0.002	1.000	0.002	1.000	3.361	0.000
Construction	0.056	0.814	0.058	0.994	0.059	0.999	2.747	0.002
Distribution	0.001	0.970	0.002	1.000	0.002	1.000	0.956	0.492
Financials	0.021	0.884	0.020	0.999	0.019	1.000	11.096	0.000
Manufacturing	0.011	0.915	0.013	1.000	0.014	1.000	1.895	0.038
Service	0.001	0.977	0.001	1.000	0.002	1.000	6.303	0.000
Transportation & Commucation	0.027	0.869	0.022	0.999	0.022	1.000	0.592	0.847
Utilities	0.015	0.903	0.016	1.000	0.016	1.000	0.070	1.000
				DY				
Market	0.022	0.882	0.023	0.999	0.024	1.000	0.796	0.654
Construction	0.100	0.753	0.098	0.983	0.113	0.995	0.100	0.753
Distribution	0.022	0.882	0.023	0.999	0.022	1.000	3.011	0.001
Financials	0.034	0.854	0.035	0.998	0.033	1.000	1.595	0.097
Manufacturing	0.016	0.900	0.017	1.000	0.017	1.000	0.578	0.858
Service	0.062	0.803	0.064	0.993	0.075	0.998	1.028	0.425

Transportation Commucation	0.069	0.793	0.072	0.990	0.072	0.999	1.267	0.242
Utilities	0.033	0.855	0.021	0.999	0.051	1.000	0.125	1.000
				EP				
Market	0.022	0.884	0.023	0.999	0.029	1.000	0.209	0.998
Construction	0.048	0.828	0.049	0.995	0.052	0.999	0.466	0.932
Distribution	0.161	0.689	0.174	0.952	0.185	0.981	0.361	0.975
Financials	0.400	0.528	0.464	0.762	0.524	0.789	14.324	0.000
Manufacturing	0.009	0.926	0.005	1.000	0.006	1.000	0.708	0.743
Service	0.017	0.897	0.011	1.000	0.012	1.000	0.623	0.821
Transportation Commucation	0.138	0.710	0.127	0.973	0.120	0.994	1.027	0.426
Utilities	0.007	0.935	0.005	1.000	0.005	1.000	0.175	0.999
				INF				
Market	21.300	0.000	6.324	0.000	5.503	0.000	5.544	0.000
				SVAR				
Market	1.497	0.223	2.765	0.029	1.913	0.081	1.035	0.419

When we consider the return series, the null hypothesis of ‘no ARCH’ is rejected for Utilities industries at the 1% significance level. A strong presence of ARCH effect is seen in predictor variables INF, BM. This is followed by predictor variables, DE, DY and EP, where the null of ‘no ARCH’ is rejected for five industries at lag twelve. Overall, the ARCH test implies that both the returns and the predictors are characterized by ARCH, and this needs to be accounted for in testing the stock return predictability.

Finally, we test for the extent of endogeneity in the predictive regression models. The results are reported in Table 7.

Table 7

Results for endogeneity tests for the aggregate market and industry portfolios. This table reports the endogeneity test results obtained through a three-step procedure. In the first step, we run the following predictive regression model: $r_t=\alpha+\beta x_{t-1}+\varepsilon_{r,t}$. Here, rt is excess return for the aggregate market or the industry portfolio, and xt is the predictor variable, which takes the form of one of the seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), and stock variance (SVAR). In the second step, we follow Westerlund and Narayan (2014) and model the predictor variable as follows: $r_t=\mu(1-\rho)+\rho x_{t-1}+\varepsilon_{x,t}$. In the third step, the relationship between the error terms is captured using the following regression: $\varepsilon_{r,t}=\gamma\varepsilon_{t-1}+\varphi_{x,t}$. If the coefficient c is statistically different from zero, then the predictor variable is endogenous. We report the coefficient on c, its test statistic and p-value. The three-step procedure is repeated for the seven economic variables.

	γ	Std. Error	*t*-Stat	*p*-Value	γ	Std. Error	*t*-Stat	*p*-Value
	BM				DE			
Market	-1.657	2.773	-0.597	0.551	-56.923	26.037	-2.186	0.030
Construction	-1.225	1.471	-0.832	0.406	-22.008	13.628	-1.615	0.108
Distribution	-0.801	1.845	-0.434	0.665	-30.474	19.306	-1.578	0.116
Financials	0.001	0.015	0.092	0.927	-33.060	18.703	-1.768	0.079
Manufacturing	-2.650	1.860	-1.425	0.156	-33.297	24.749	-1.345	0.180
Service	0.261	2.900	0.090	0.928	-47.547	25.965	-1.831	0.069
Transportation Commucation	0.030	1.747	0.017	0.986	15.327	19.894	0.770	0.442
Utilities	-2.917	3.061	-0.953	0.342	-16.881	13.702	-1.232	0.220
	DP				DY			
Market	-17.133	11.847	-1.446	0.150	-11.797	9.194	-1.283	0.201
Construction	-2.805	9.296	-0.302	0.763	4.413	7.579	0.582	0.561
Distribution	-14.760	10.628	-1.389	0.167	6.464	7.101	0.910	0.364
Financials	-11.175	8.060	-1.387	0.167	2.517	7.849	0.321	0.749
Manufacturing	-10.270	12.469	-0.824	0.411	-2.086	9.039	-0.231	0.818
Service	-8.737	10.603	-0.824	0.411	-4.132	6.758	-0.611	0.542
Transportation Commucation	4.275	9.754	0.438	0.662	-6.861	10.773	-0.637	0.525
Utilities	-21.599	10.730	-2.013	0.046	-5.900	8.017	-0.736	0.463
	EP				INF			
Market	-56.923	26.037	-2.186	0.030	27.041	143.944	0.188	0.851
Construction	13.407	11.784	1.138	0.257	16.931	187.010	0.091	0.928
Distribution	15.627	11.741	1.331	0.185	89.376	142.518	0.627	0.531
Financials	-8.708	10.873	-0.801	0.424	-67.564	175.310	-0.385	0.700

Manufacturing	0.513	14.717	0.035	0.972	66.194	136.415	0.485	0.628
Service	4.850	11.494	0.422	0.674	-23.876	140.993	-0.169	0.866
Transportation Commucation	3.141	7.115	0.441	0.659	52.225	155.435	0.336	0.737
Utilities	-10.244	12.357	-0.829	0.408	26.491	119.955	0.221	0.826
	SVAR							
Market	-599.533	80.427	-7.454	0.000				
Construction	-569.274	110.783	-5.139	0.000				
Distribution	-617.219	77.683	-7.945	0.000				
Financials	-668.926	101.156	-6.613	0.000				
Manufacturing	-609.024	73.366	-8.301	0.000				
Service	-631.837	76.169	-8.295	0.000				
Transportation Commucation	-594.863	87.900	-6.767	0.000				
Utilities	-508.129	65.497	-7.758	0.000				

We report the coefficient on γ, the *t*-test statistic associated with the null hypothesis that γ = 0, and the resulting *p*-value. The predictors SVAR is endogenous. The null hypothesis that γ = 0 is not rejected mostly at the 1% significance level for these predictors, both at the market and industry levels. The main message emerging from the preliminary analysis of the data is that most of the predictor variables are persistent, and characterized by the presence of strong ARCH effects. These issues need to be accounted for in the predictive regression model. This motivates us to use the WN procedure for in-sample predictability tests.

3.2. In-sample predictability test results

In this section, we examine in-sample evidence of stock return predictability. We begin with the WN test, for which we report the 95% confidence interval for β based on both the asymptotic FQGLS *t*-test as well as the sub-sample FQGLS *t*-test. We can interpret that when the confidence interval includes the value zero, we cannot reject the null hypothesis of no predictability. Aggregate market and industry portfolio excess returns, Table 8 reports the in-sample predictability results for the aggregate market and for each of the seven industries.

Table 8

In-sample predictability test results for the aggregate market and industry portfolio excess returns. This table reports the in-sample predictability test results for the aggregate market and seven industries based on the following regression model: $r_t=\alpha+\beta x_{t-1}+ \varepsilon_{r,t}$ Here, rt is excess return for the aggregate market or the industry portfolio, and xt is the predictor variable, which takes the form of one of the seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), and stock variance (SVAR). We employ the following Westerlund and Narayan (2012, 2014) FQGLS-based *t*-statistic

$$t_{FQGLS}=\frac{\sum_{t=q_m+2}^{T}\pi_t^2 x_{t-1}^d r_t^d}{\sqrt{\sum_{t=q_m+2}^{T}\pi_t^2\left(x_{t-1}^d\right)^2}}$$

We report the 95% confidence interval for β based on the asymptotic FQGLS test (t_{FQGLS}). The estimation covers the sample period 2000:07–2015:6. When the confidence interval includes the value zero, we cannot reject the null of no predictability.

	BM	DE	DP
Market	[0.632844 0.762756]	[0.024206 0.089794]	[0.018324 0.079276]

Construction	[0.516943 0.656257]	[0.511516 0.651084]	[0.031332 0.101868]
Distribution	[0.052319 0.134681]	[-0.00481 0.011412]	[-0.00358 0.026581]
Financials	[0.407741 0.549059]	[0.002351 0.045649]	[0.044055 0.122145]
Manufacturing	[0.488769 0.629231]	[-0.00241 0.031409]	[-0.00249 0.031094]
Service	[0.077548 0.170852]	[-0.00254 0.030936]	[0.003664 0.048936]
Transportation and Communication	[-0.00215 0.00275]	[-0.00266 0.003662]	[-0.0018 0.0022]
Utilities	[-0.0013 0.001514]	[0.005384 0.053016]	[0.182424 0.303776]

Table 8 (*continued*)

	DY	EP	INF
Market	[0.04437 0.12263]	[0.024206 0.089794]	[-0.00206 0.032662]
Construction	[0.191691 0.314709]	[0.120287 0.227513]	[0.114504 0.220096]
Distribution	[-0.00266 0.003662]	[0.655527 0.782673]	[0.43518 0.57662]
Financials	[-0.00175 0.033749]	[0.244863 0.375737]	[-0.00413 0.023734]
Manufacturing	[0.003375 0.048225]	[0.004368 0.050632]	[0.620879 0.752121]
Service	[0.099837 0.200963]	[0.05919 0.14481]	[0.231242 0.360358]
Transportation and Communication	[0.001741 0.044059]	[0.591317 0.725483]	[-0.00481 0.018609]
Utilities	[0.028931 0.097869]	[-0.00131 0.001514]	[0.956086 0.998314]
	SVAR		
Market	[-0.00497 0.015766]		
Construction	[0.010692 0.064508]		
Distribution	[-0.00258 0.030778]		
Financials	[0.002632 0.046368]		
Manufacturing	[-0.0041 0.023904]		
Service	[-5.9E-05 0.039059]		
Transportation and Communication	[-0.00131 0.001514]		
Utilities	[-0.00453 0.021133]		

For the aggregate market, we find that five variables (BM, DE, DP, DY and EP) predict aggregate market returns. There is no evidence that SVAR predict market returns. This is consistent with the evidence found in the existing literature for the US market (Lewellen, 2004; Campbell and Thompson, 2008). The existing empirical evidence is strongly in favor of BM, EP and DY as the most popular predictor of market returns. Our findings on industry portfolio excess return predictability highlight important differences in predictability across industries. This can be summarized as follows:

- EP predicts excess returns for all the six industries. This is also one of the economic variable that predicts aggregate market excess returns.

- BM and DY predicts excess returns for five industries, namely, BM predicts excess returns for Construction, financials, Distribution, Manufacturing, Service; and DY predicts excess returns for Construction, Manufacturing, Service, Utilities and Transportation and Communication. Predictors DP, DE, and INF each predict excess returns for four industries.

- The economic variables that have the least predictive ability is SVAR.

3.3 Out-of-sample predictability tests

In this section, we examine out-of-sample predictability of returns from all the seven economic variables used as predictors. We also compute mean combination forecasts – the average of the return forecasts from the seven individual predictive regression models and examine their performance against the historical mean model.

We now turn to the out-of-sample predictability results of Aggregate market and industry portfolio excess returns, which are reported in Tables 9, respectively, for the aggregate market and industry portfolios. We begin with predictability of market and industry excess returns reported in Table 9.

Table 9

Out-of-sample forecast evaluation results for the aggregate market and industry portfolio excess returns. This table reports the out-of-sample forecast performance results for the traditional predictive regression model against the benchmark historical mean model for the 2010:07–2015:06 out-of-sample period. The predictive regression model is given by $r_t=\alpha+\beta x_{t-1}+\varepsilon_{r,t}$. Here, rt is excess return for the aggregate market or industry portfolio, and xt is the predictor variable, which takes the form of one of the seven economic variables, namely, book-to-market (BM), dividend payout (DE), dividend-price (DP), dividend yield (DY), earnings-price (EP), inflation (INF), or stock variance (SVAR). The out-of-sample period is 20% of the full sample. One-step ahead out-of-sample forecasts are generated recursively. We report six forecast evaluation metrics, namely, relative mean absolute error (RMAE), relative root mean squared error (RRMSE), Campbell and Thompson (2008) out-of-sample R2 (OR^2), Mincer Zarnowitz R^2(RMZ), and relative success ratio (RSR). RMAE and RRMSE values less than one, RMZ and RSR values greater than one, and $OR^2 > 0$, indicate that predictive regression model out-performs historical mean model.

BM					
	RMAE	RRMSE	OR^2 (%)	RMZ	RSR
Market	0.9003	0.9220	-0.7850	5.7132	1.0295
Service	0.9925	0.9423	0.4120	3.4910	1.0333
Financials	0.9836	0.8378	-1.2110	0.0090	1.0288
Manufacturing	0.9764	0.8905	1.2753	21.6331	1.0367
Construction	0.9327	0.8532	0.1628	15.4852	1.0225
Distribution	0.9213	0.8817	-1.1681	3.3370	1.0212
Transportation and Communication	0.9210	0.8332	-1.1490	4.3326	1.0021
DE					
	RMAE	RRMSE	OR^2 (%)	RMZ	RSR
Market	0.9620	0.8849	1.3112	8.1633	1.1314
Service	0.9522	0.8717	1.6712	0.1432	0.1536
Financials	0.9473	0.8645	1.0010	6.7466	0.1107
Manufacturing	0.9421	0.8913	1.7843	4.3499	0.0938

Construction	0.9055	0.8575	-0.1778	19.5327	1.0854
Distribution	0.9283	0.8430	-1.4815	7.1417	0.0919
Transportation and Communication	0.9433	0.8214	-0.8395	2.8400	1.1235
DP					
	RMAE	RRMSE	OR^2 (%)	RMZ	RSR
Market	0.9620	0.9735	-0.9800	3.4910	1.0370
Service	0.9982	0.9881	0.0128	1.4458	1.0333
Financials	0.9763	0.8932	-0.4011	4.3499	0.0288
Manufacturing	0.9800	0.8894	-0.9430	1.9533	0.0367
Construction	0.9532	0.7878	-0.1778	3.5876	1.0225
Distribution	0.9445	0.8810	-0.2240	0.4218	0.0524
Transportation and Communication	0.9312	0.8230	0.2853	6.4532	0.6552

Table 9 (*continue*d)

EP					
	RMAE	RRMSE	OR^2 (%)	RMZ	RSR
Market	0.9452	0.8567	2.6450	0.4710	0.8734
Service	0.9423	0.8813	-0.6712	1.8648	1.0463
Financials	0.8378	0.8345	0.0010	11.2586	1.0193
Manufacturing	0.8905	0.8624	2.3343	7.6524	1.4922
Construction	0.8532	0.8126	-0.1338	7.1429	0.0078
Distribution	0.8817	0.8267	-1.8986	0.5714	1.0251
Transportation and Communication	0.9833	0.8817	-0.0395	12.8338	1.0341
INF					
	RMAE	RRMSE	OR^2 (%)	RMZ	RSR
Market	0.9267	0.8936	0.3010	5.6428	1.4017
Service	0.9780	0.9124	0.1019	2.8571	1.3324
Financials	0.8014	0.8001	2.2010	3.2429	1.0023
Manufacturing	0.9338	0.8905	1.6648	18.3470	0.3256
Construction	0.9731	0.8132	-0.1332	7.1429	0.0078
Distribution	0.8910	0.8217	-1.4811	0.0714	1.3254
Transportation and Communication	0.9285	0.9214	-0.8425	0.2844	0.2998
Svar					
	RMAE	RRMSE	OR^2 (%)	RMZ	RSR
Market	1.0053	1.0160	-2.9677	1.4286	0.0040
Service	1.0070	0.9780	1.3290	0.3516	0.3067
Financials	1.0042	0.9801	1.0280	0.7454	0.2133
Manufacturing	0.9338	0.9167	0.7921	0.1392	1.2056
Construction	0.9731	0.9532	0.7899	0.0004	1.2083
Distribution	0.9338	0.9224	-0.0079	0.9268	0.2152
Transportation and Communication	0.9780	0.8321	-0.0033	0.3206	0.0900

The evidence of out-of-sample predictability for aggregate market is very strong, in that all the six metrics support predictability for the DE, DP, DY and EP-based predictive regression models. For BM-based predictive regression model, only one metric supports predictability.

The out-of-sample results for the aggregate market match reasonably well with the in-sample results. We also find significant evidence of out-of-sample predictability for the industries. This can be summarized as below:

- DE turns out to be the most popular out-of-sample predictor of industry returns. At least four of the six metrics reveal that the DE based predictive regression model beats the historical average model in four out of seven industries.
- The most predictable industries are financials, manufacturing where there are at least four predictors with at least five evaluation metrics that support the predictive regression model.

4. Conclusion

In this paper we undertake an extensive empirical investigation of predictability and profitability in the Korean stock market for the aggregate market portfolio and its components that include industries. Our findings suggest that Korean stock market are predictable although predictability is industry-specific. In-sample evidence of heterogeneous predictability is corroborated by an out-of-sample forecasting evaluation. Predictability and profits are therefore heterogeneous. The combination forecasts pick up economically meaningful changes in all the seven economic variables and significantly improve the out-of-sample forecasting performance relative to individual predictive regression models.

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