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The Role of a Mispricing Factor in Korean Stock Market

한국 주식시장에서 가격설정오류 요인의 역할

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이 용 우

Abstract

The Role of a Mispricing Factor in Korean Stock Market

YongWoo Lee

College of Business Administration

Graduate School of Seoul National University

This paper finds that a three-factor model with a “mispricing” factor along with size and market factors, proposed by Yuan and Stambaugh (2017), has a superior ability in accommodating anomalies in KOSPI market over prominent four- and five-factor alternative models, yet not in TOTAL and KOSDAQ market. The mispricing factor combines information across 3 notable anomalies in TOTAL and KOSPI market, and 6 anomalies in KOSDAQ market by averaging rankings of anomalies. In addition, the result show that the investor sentiment has no effect on anomalies in Korea despite the fact that Korean stock market bears more short-sale risk and constraints than the U.S. stock market.

Key words: anomaly, investor sentiment, mispricing factor

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1. Introduction

Beginning with the CAPM of Sharpe (1964) and Lintner (1965), the asset pricing models have been studied for a long time. The CAPM insist that a market portfolio explains stock movement, yet it has been revealed that the argument barely stand in numerous empirical studies. For instance, Fama and French (1993) point out that the market factor is not sufficient in demonstrating stock returns and that additional size and value-versus-growth measures with a market factor provide a better explanatory power. Since then an exploration of a new anomaly violating the three-factor model of Fama and French (1993) has proceeded. Jegadeesh and Titman (1993) find the momentum anomaly meeting such criterion, and Carhart (1997) turn the momentum anomaly into a new factor and add it to the three-factor model of Fama and French (1993). As further anomalies have been found, the demand for an alternative factor model that can accommodate more anomalies has augmented.

As with the momentum anomaly, many studies confirm that profitability and investment anomalies are two conspicuous phenomena existing in stock market. Titman, Wei, and Xie (2004) and Xing (2008) find that high investment predicts abnormally low returns, while Fama and French (2006) and Novy-Marx (2013) show that high profitability predicts abnormally high returns. In this context, two additional factors related to investment and profitability anomaly have been recently developed. Hou, Xue, and Zhang (2015a) create a four-factor model that combines a market and size factor with return on equity and investment-to-asset factor. Fama and French (2015) extend their three-factor model to a five-factor model with slightly different versions of profitability and investment factors accompanied by the existing market, size, and book-to-market factor.

Stambaugh and Yu (2017) propose a four-factor model with the two mispricing factors along with a market and size factor. When constructing mispricing factors, they take a different approach to factor construction. Instead of forming a factor solely based on one anomaly, they aggregate information in multiple anomalies. That is, they construct a factor by averaging rankings multiple anomalies, rather than create a factor using stocks' rankings on a single anomaly. They use an average to attain a less noisy measure of a stock's mispricing, which make more precise identification possible in choosing which stocks to long and short when constructing a factor that can better explain anomalies reflecting mispricing. Stambaugh and Yu (2017) show that their mispricing factor model's ability to accommodate a wide range of anomalies surpasses that of both the four-factor model of Hou, Xue, and Zhang (2015a) and the five-factor model of Fama and French (2015). They also confirm that investor sentiment predicts the mispricing factors, especially short legs, consistent with the asymmetry in ease of buying versus shorting.

In this research, I examine the mispricing factor's ability to accommodate a large set of anomalies in Korean stock market compared to notable four- and five-factor alternative models, and the predictability of investor sentiment on mispricing factors. I hypothesize that the mispricing factor model outperform in accommodating a range of anomalies than the q-factor model of Hou, Xue, and Zhang (2015a) and the five-factor model of Fama and French (2015). In addition, according to Uk, Eom, and Park (2016), Korean stock market bears more short-sale risk and constraints than the U.S. stock market, due to stricter short sale regulations. Hence, I also hypothesize that investor sentiment in Korean stock market predicts mispricing factor stronger than in the US setting.

I construct a mispricing factor, and develop a three-factor model (henceforth M-3), in addition to a market and size factor, with a mispricing factor. In constructing the mispricing factor, I use only 3 or 6 anomalies rather than 11 anomalies as opposed to Stambaugh and Yu (2017) in each different market. I find that the set of 3 among 11 anomalies examined by Stambaugh, Yu, and Yuan (2012, 2014, 2015) are not captured by the three-factor model of Fama and French (1993) in TOTAL and KOSPI market, and 6 anomalies are not explained in KOSDAQ market. TOTAL market indicates a combined market of KOSPI and KOSDAQ. I applied the same approach of Stambaugh and Yu (2017) by constructing a factor from the set of 3 and 6 anomalies, and averaging rankings of the anomalies.

The M-3 model has a superior ability in accommodating the 3 set of anomalies than both the four-factor model of Hou, Xue, and Zhang (2015a) and the five-factor model of Fama and French (2015) in KOSPI market. The four-factor model of Hou, Xue, and Zhang (2015a) has the greatest ability in explaining the 3 and 6 set of anomalies in TOTAL and KOSDAQ market, respectively, and the M-3 model takes the second place. For example, throughout the entire sample period, the Gibbons-Ross-Shaken (1989) test of whether all the 3 anomalies' alphas equal zero produces a p-value of 0.454, for the M-3 model compared to 0.051 or less in KOSPI market for these four- and five-factor alternative models. On the contrary, the GRS p-value of 0.016 for model M-3 is less than that of 0.029 for the four-factor model in TOTAL market. The GRS test of whether all the 6 anomalies' alphas equal zero produces a p-value of 1.1E-05 compared to 1.2E-05 in KOSDAQ market for the four-factor model. When using a larger set of 17 anomalies in each different market, I draw similar results. The M-3 model has the utmost ability in explaining larger set of 17 anomalies only in KOSPI market, but not in TOTAL and KOSDAQ market. When judging the abilities of models to explain each other's factors, the four-factor model of Hou, Xue, and Zhang (2015a) performs better than other alternative models in the three markets.

In addition, the results show that investor sentiment does not predict the mispricing factor at all. In order to investigate the reason for the results, I check the effects of investor sentiment on anomalies and find that the sentiment has little influence on anomalies. The long-short portfolio of each 11 anomalies employed by Stambaugh, Yu, and Yuan (2012, 2014, 2015) has no significant relation with the lagged investor sentiment index in TOTAL and KOSPI market, and the long-short portfolio of 4 anomalies does have significant relation with the sentiment index in KOSDAQ market. Yet, the sign of the investor sentiment's coefficients is spurious. The investor sentiment has negative relations with asset growth and investment-to-asset anomalies, and positive with bankruptcy probability and return on assets anomalies.

The main contribution of this study is to suggest a parsimonious factor model. The three-factor model based on a mispricing factor accommodates a range of anomalies in KOSPI market better than the four-factor model of Hou, Xue, and Zhang (2015a) and the five-factor model of Fama and French (2015). This paper also confirms that the q-factor model of Hou, Xue, and Zhang (2015a) outperforms the five-factor model of Fama and French (2015) in capturing a quantity of anomalies in Korean stock market. In addition, this paper finds that anomalies in Korea barely reflect mispricing and investor sentiment.

This paper is organized as follows. Section 2 discusses the linkage between anomalies and mispricing, and sentiment. Section 3 describes sample and key variables. Section 4 elaborates the construction of the mispricing factor model and examines their empirical characteristics. Section 5 compares the mispricing factor model to four-factor and five-factor alternative models. Lastly, Section 6 concludes the paper.

2. Anomalies, mispricing, and sentiment

The fundamental motivation of linking anomalies and mispricing is that anomalies partly reflect mispricing and that mispricing has systematic effects across stocks, often characterized as investor sentiment. Baker and Wurgler (2006) find that market-wide sentiment is a common factor influencing cross-sectional returns across stocks. Evidence for short-sale impediments that prevents the correction of stock prices resulting in arbitrage asymmetry among overpriced and underpriced stocks are provided by numerous studies, for example by Shleifer and Vishny (1997).

Stambaugh, Yu, and Yuan (2012) explore a prominent subset of the many anomalies reported in the literature and find 11 anomalies that survive adjustment for exposures to the three-factor model of Fama and French (1993). Consistent with the above two combining findings, they confirm that the short-leg returns for long-short spreads associated with each of 11 anomalies are significantly lower following a high level of investor sentiment as measured by the Baker-Wurgler sentiment index. To clarify, a high sentiment means that investors are optimistic about the future economic movement and a low sentiment means that investors are pessimistic, and thus, a high sentiment causes stocks overpriced and a low sentiment leads to stocks underpriced.

In addition, Stambaugh, Yu, and Yuan (2015) find that idiosyncratic volatility (IVOL) represents arbitrage risk deterring the correction of sentiment-related mispricing, and mispricing should get less corrected among stocks with high IVOL. The negative (positive) IVOL-return relation among overpriced (underpriced) stocks should therefore be stronger following a high (low) level of the Baker-Wurgler sentiment index. On these bases, Stambaugh and Yuan (2017) develop a four-factor model, based on the same 11 anomalies they used in the previous studies, targeted at capturing common components of mispricing effects, which is investor sentiment.

According to Uk, Eom, and Park (2016), Korean stock market bears more short-sale risk and constraints than the U.S. stock market. This is because Korean stock market regulator only allows covered short selling through loan transaction and prohibits naked short selling, and the margin ratio for short sales is high, which begins generally from 200% at the short-sale point. These regulations result in greater magnitude of asymmetry in ease of buying and shorting than that in the US. Consequently, it might be reasonable to expect that the short-leg returns for long short-spreads associated with anomalies should be lower in Korean stock market than in the US. In other words, it means that investor sentiment more affects mispricing factor in Korea. Yet, the result shows that the investor sentiment has no effect on anomalies in Korean stock market.

3. Sample and Key variables

3.1 Data and playing fields

The data is collected from Dataguide for market data and common stocks listed or delisted on KOSPI and KOSDAQ market, and from TS-2000 for accounting data for the sample firms. The sample period is from August 2001 to December 2016, and the sample begins from 2001 because it is arguably the time for Korean economy to finish a structural reformation after the 1997 IMF crisis. I exclude stocks worth less than ₩1,000 to remove a penny stock effect and use ordinary common shares. I also delete stocks with return values missing and with annual (or quarterly) asset and sales values zero or missing.

The playing fields are three different markets; KOSPI, KOSDAQ market, and TOTAL market combining KOSPI and KOSDAQ market. I confirm only three anomalies survive exposure for the three-factor model of Fama and French (1993) in TOTAL and KOSPI market, and six anomalies do in KOSDAQ market among 11 anomalies investigated in Stambaugh, Yu, and Yuan (2012). The following are the three anomalies present in TOTAL and KOSPI market: financial distress probability by Campbell, Hischer, and Szilagyi (2008), O-score bankruptcy probability by Olson (1980), and return on assets by Wang and Yu (2013). The following are the six anomalies present in KOSDAQ market: composite equity issues by Daniel and Titman (2006), accruals by Sloan (1996), gross profitability premium by Novy-Marx (2013) and the three same anomalies used in the previous markets. I substitute O-score and the failure probability for LOGIT and HAZARD models, respectively, because O-score and the failure probability are not applicable in Korean market. Lee and Kim (2015) propose LOGIT and HAZARD models showing better distress predictability compared to the original O-score and the failure probability in Korean market.

3.2 Investor sentiment index

I measure investor sentiment using the monthly market-based sentiment series constructed by Kim and Byun (2010)[1]. They develop the investor sentiment index applied in Korean stock market following the same procedure of Baker and Wurgler (2006). They form their composite index by taking the first principal component of six measures of investor sentiment. In contrary to Baker and Wurgler (2006), due to data limitation in Korea, they replace four measures of proxies of sentiment. Six measure they use are the monthly trading imbalance of individual investors, the monthly stock fund flow ratio, the Customer Expectation Index for the business cycle, customers' deposits for stock investment, the turnover ratio in the Korea Exchange, and the equity share in new issues. The investor sentiment index spans over 12 years, from January 1999 to December 2010. The investor sentiment index of Kim and Byun (2010) is plotted in Fig. 1. It appears to capture major accounts of fluctuations in sentiment. The internet bubble dramatically amplified the sentiment in 1999 and the sentiment fell in accordance with the bubble collapsed. The sentiment dropped in 2004 due to exchange rate shock caused by the weak dollar. When North Korea conducted the first nuclear experiment in 2006, the sentiment plunged. In 2009, the aftermath of the 2008 financial crisis again crushed the sentiment.

[INSERT FIGURE 1 HERE]

[1]I am very grateful to Kim for providing time series of their investor sentiment index.

4. The mispricing factor model

4.1 The mispricing factor and size factor

The main motivation of this research is to find a parsimonious model that includes a mispricing factor aggregating information from a variety of anomalies. I construct a three-factor model that includes a mispricing factor along with size and market factor.

The excess value-weighted market return is the first factor in the model. In order to construct the remaining a size factor and mispricing factor, I average stocks' rankings with respect to various anomalies. The approach that averages anomaly rankings stands in contrast to previous approaches that construct a factor by ranking on a single return anomaly. As Stambaugh and Yuan (2017) mentioned, aggregating various information into a factor may not be a proper method in case the one anomaly uniquely captures a systemic risk and mispricing, because it pollutes that anomaly with superfluous information. The new approach, however, can work better if that anomaly is not uniquely valuable. The empirical results show that the new approach works in KOSPI market but not in TOTAL and KOSDAQ market.

I use 3 anomalies in TOTAL and KOSPI market, and 6 anomalies in KOSDAQ market. Among the 6 anomalies that survive in KOSDAQ market, the three anomalies do also exist in TOTAL and KOSPI market. Hence, 6 anomalies in total are used in the research. The 6 anomalies employed in the model are briefly described in the Appendix: financial distress, bankruptcy probability, and return on assets exist in TOTAL and KOSPI market, and composite equity issues, accruals, and gross profitability premium are additionally present in KOSDAQ market. I rank firms each month by an anomaly in deciles, and stocks with the highest rank means that they are the most overpriced and those with the lowest rank means that they are the most underpriced.

Next, I compute equal weighted average of a stock's rankings with regard to the available anomaly measures. Hence, each month a stock has one composite mispricing measure, CM. Diversification effect is the rationale behind for averaging. It renders a stock's average rank have a less noisy measure of its mispricing than does its rank with regard to any single anomaly. Plus, when calculating the CM, the reason for putting an equal weight on each anomaly ranking is to provide a simple, transparent, and not sample-dependent measure.

I exclude stocks whose prices are less than ₩1,000. Additionally, stocks with return values missing, and with annual (or quarterly) asset and sales values zero or missing are also removed. Thereafter, I construct the mispricing factor by applying a 2×3 sorting procedure following the one employed in Fama and French (2015). To be specific, each month I sort stocks by size (equity market capitalization) and separate them into two groups using the KOSPI and KOSDAQ median size as breakpoint in each different field (the KOSPI median size used as a breakpoint in TOTAL market). Independently, I classify all stocks by CM and assign them to three groups using as breakpoints the 20th and 80th percentiles of the KOSPI and KOSDAQ market in each separate market, and the combined KOSPI and KOSDAQ universe in TOTAL market. As a result, I obtain six different groups in each playing field in each month. In order to construct the mispricing factor, UMO, I calculate value-weighted returns on each of the four portfolios, which are small-cap low CM, small-cap high CM, large-cap low CM, and large-cap high CM portfolios. The value of UMO for a given month is the simple average of the returns on the two low-CM portfolios minus the average of the returns on the two high-CM portfolios.

As Stambaugh and Yuan (2017) do, I use the 20th and 80th percentiles of the market as breakpoints of CM rather than the 30th and 70th percentiles of the market, used in factor construction by Fama and French (1993, 2015) and Hou, Xue, and Zhang (2015a). The reason for the alteration is that relative mispricing in the cross-section is likely to be more conspicuous in the extremes than the middle. Stambaugh, Yu, and Yuan (2015) show that the negative (positive) effects of idiosyncratic volatility for overpriced (underpriced) stocks are in accord with the presence of arbitrate risk preventing the correction of mispricing, and they empirically demonstrate that such effects exist largely in extremes of a composite mispricing measure and are stronger for smaller stocks.

As in Stambaugh and Yuan (2017), I construct a size factor only with the stocks not used in forming the mispricing factor, UMO, in a given month. To construct the size factor, SMB, I calculate the value-weighted returns of the stocks present in small-cap middle CM and large-cap middle CM. The value of SMB in a given month becomes the return on the small-cap middle groups minus the large-cap middle groups.

A conventional way of computing SMB, as Fama and French (2015) do, would be the simple average of the value-weighted returns on the three small-cap portfolios minus the simple average of the value-weighted returns on the three large-cap portfolios. The purpose of averaging three mispricing groups would seek to neutralize the influence of mispricing in computing SMB. Yet, the neutralization would not be attainable due to arbitrage asymmetry, a greater capability or willingness to buy stocks than short for investors. Thus, arbitrage asymmetry renders the mispricing within the overpriced group more serious than the mispricing within the underpriced group. In addition, this asymmetry is possibly to be more severe for small stocks than for large ones because small stocks contain greater arbitrage risk such as idiosyncratic volatility. This would make SMB have an overpricing bias if I calculated SMB in the conventional way. Therefore, when computing SMB it would be more reasonable to use stocks solely from the middle of the mispricing sort so as to decrease the influence of arbitrage asymmetry and achieve the neutralization.

Table 1 shows means, standard deviations, and correlations for monthly series of the three factors in the mispricing factor model. (MKT_total, MKT_kospi, and MKT_kosdaq denotes the excess market return of TOTAL, KOSPI and KOSDAQ, respectively, these notations will be kept throughout the paper.) The empirical analysis in each TOTAL, KOSPI, and KOSDAQ market will be reported in a row throughout the paper.

[INSERT TABLE 1 HERE]

4.2 Factor betas, arbitrage asymmetry, and sentiment effects

Table 2 reports parameter estimates from the M-3 model for the individual long-short spreads based on the anomaly measures used above. Panel A contains the alphas and factor loadings of the long-short returns between the value-weighted portfolios of stocks in the long leg (bottom decile) and short leg (top decile). Panel B provides corresponding estimates for the long legs, and Panel C gives estimates for the short legs. In case of TOTAL market, the size and mispricing measure breakpoints are based on KOSPI deciles. Stocks worth less than ₩1,000 are deleted. In addition, stocks with return values missing and with annual (or quarterly) asset and sales values zero or missing are deleted.

Alpha of return on asset in long-short spreads is significant in TOTAL and KOSPI market, and alphas of composite equity issues, bankruptcy probability, and gross profitability premium in long-short spreads are significant in KOSDAQ market. The long-short betas on the mispricing factor, UMO, are positive with t-statistics between 7.11 and 11.06 in TOTAL, 6.19 and 7.76 in KOSPI, and 1.47 and 11.15 in KOSDAQ market. These results confirm that averaging anomaly rankings produces a factor that captures common variation in returns for the anomalies. Not surprisingly, for each anomaly with respect to its corresponding factor, the short-leg beta is significantly negative, and the long-leg beta is significantly positive, with the long leg for accruals in KOSDAQ market being the only exception.

[INSERT TABLE 2 HERE]

It is also detected that the short-leg betas are generally larger in absolute magnitude than their long-leg counterparts in all the three markets. The average long-leg UMO beta is 0.15, 0.16, and 0.18 in TOTAL, KOSPI, and KOSDAQ market, whereas the average short-leg UMO beta is -0.64, 0.65, and -0.49 in the corresponding markets. These results may imply that the mispricing factor indeed captures systematic components of mispricing. Because the arbitrage asymmetry deters the correction of mispricing in overpriced (short-leg) stocks much more than in underpriced (long-leg) stocks, a greater short-leg sensitivity to systematic mispricing would be the outcome of arbitrage asymmetry in consort with investor sentiment.

Yet, the table 3 shows that the mispricing factor has little relationship with the investor sentiment. Table 3 gives the parameters from the time-series regression of each factor as well as its long and short legs in the mispricing factor model on the previous month's level of investor sentiment of Kim and Byun (2010). The t-statistics for the lagged investor sentiment index on the mispricing factor are 0.14, -0.11, and 0.24 in each three markets. The t-statistics of long-leg of UMO are generally greater than those of short-leg. It means that the investor sentiment does not predict the mispricing factor at all. These results reveal that the argument of Stambaugh, Yu, and Yuan (2012) is not suitable in Korean stock market. They state that the arbitrage asymmetry mechanism explained by short-sale impediments is one essential reason to prevent investors shorting stocks. Accordingly, overpriced stocks caused by high investor sentiment have less corrected than does underpriced stocks caused by low sentiment.

[INSERT TABLE 3 HERE]

To dig out the reason for this phenomenon further, I regress each anomaly's excess long and short leg, and long-short difference on the previous month's investor sentiment index as Stambaugh, Yu, and Yuan (2012) do in their studying. I obtain the similar outcomes as above[2]. I cannot find the uniform phenomenon that the slope coefficients on short-legs are larger than those on long-legs. The t-statistics for the lagged investor sentiment index on each long-short anomaly are not significant except bankruptcy probability and return on assets in KOSDAQ market.

According to Hwang (2017), the average daily short-selling volume ratio is 1.09% in KOSPI market and 0.30% in KOSDAQ market, and the average daily short-selling trading value ratio is 3.11% in KOSPI market and 0.96% in KOSDAQ market from July 2008 to April 2016. Such a low portion of short-sale volume and trading value in Korean stock market signal that short-sale does not have a substantial effect on stock price in the market level. This may be a reason for no predictability of investor sentiment index on anomalies and the mispricing factor.

5. Comparing factor models

In this part, the mispricing factor will be evaluated relative to the three-factor and five-factor model of Fama and French (1993, 2016) and the four-factor model of Hou, Xue, and Zhang (2015a). Subsection 5.1 reports the comparison of models' relative abilities to explain various individual anomalies, both the set of 3 and 6 anomalies examined in Table 2 as well as the substantially wider set of 17 anomalies. In subsection 5.2, I conduct pairwise model comparisons that evaluate each model's ability to explain factors present in another. Robustness test is presented in subsection 5.3.

5.1 Comparing models' abilities to explain anomalies

[2] The outcomes are not reported but available upon request.

Table 4 reports alphas and t-statistics from the different factor models for each of the 3 and 6 anomalies used in the mispricing factor in TOTAL and KOSPI market, and in KOSDAQ market, respectively. For convenience, the factor models are denoted as follows:

FF-3: three-factor model of Fama and French (1993)

FF-5: five-factor model of Fama and French (2015)

q-4: four-factor "q-factor" model of Hou, Xue, and Zhang (2015a)

M-3: three-factor mispricing factor model introduced in this paper

For each anomaly, long-short spread is constructed by the return on the value-weighted portfolio of stocks in the lowest decile of the anomaly measure minus the return on those in the highest decile. (The highest decile matches with the most overpriced, and thus corresponds to the lowest three-factor Fama-French (1993) alpha.) To compare various model's abilities to explain anomalies, I run 3 and 6 regressions of the form

$$R_{i,t} = \alpha_i + \sum_{j=1}^{K} \beta_{i,j} F_{j,t} + u_{i,t}, \quad (1)$$

where the $F_{j,t}$'s are the K factors in a given model. Each long-short spread is used as the dependent variables in the regression. Panel A shows the estimated α_i's for each model and Panel B shows the corresponding t-statistics. The averages of the $R_{i,t}$ is also reported in the first column in the table.

Given that all FF-3 alphas are economically and statistically significant, it corresponds to the fact that anomalies have been identified with regard to the FF-3 model. In all the three markets, the FF-3 and FF-5 generally show inferior ability to accommodate anomalies compared to q-4 and M-3. Plus, the FF-5 model produces slightly better results than the FF-3. Yet all the anomalies, except gross profitability premium in KOSDAQ market, still remain significant in the FF-5 model, the magnitude of every alpha becomes lower in FF-5 model in the three markets. The FF-3 alphas range from 1.38% (bankruptcy probability) to 2.176% (return on assets) in TOTAL, 2.099% (bankruptcy probability) to 2.563% (return on assets) in KOSPI, and 1.39% (accruals) to 4.434% (return on assets) in KOSDAQ market. The FF-5 alphas range from 1.147% (bankruptcy probability) to 1.729% (return on assets) in TOTAL, 1.892% (bankruptcy probability) to 2.218% (return on assets), and 0.937% (gross profitability premium) to 3.629% (return on assets).

[INSERT TABLE 4 HERE]

In comparing model q-4 and M-3, it is difficult to judge which model has an exceeding ability. One anomaly appears economically and statistically significant in one model, but it becomes insignificant in the other model. For instance, bankruptcy probability is significant in model q-4 and its alpha is 1.099% with the t-statistics of 2.44, yet the anomaly becomes insignificant in model M-3 and its alpha is -0.266% with the t-statistics of -0.78 in TOTAL market. On the other hand, return on assets is significant in model M-3 and its alpha is 1.404% with the t-statistics of 1.76, yet it becomes insignificant in model q-4 and its alpha is -0.167 with the t-statistics of -0.39 in TOTAL market. A similar pattern is observed with the bankruptcy probability and return on assets in KOSPI market. In KOSDAQ market, failure probability and return on assets show significance in model q-4 with its alphas being

2.346% and 1.878% and its t-statistics being 2.67 and 2.72, whereas they turn out to be insignificant in model M-3 with its alphas being 0.381% and 0.274% and its t-statistics being 0.59 and 0.5, respectively. Bankruptcy probability and gross profitability premium are significant in model M-3 and its alphas are -1.388% and -1.051% with the t-statistics of -3.06 and -2.33, while they become insignificant in model q-4 and its alphas are 0.537% and 0.574% with the t-statistics of 0.79 and 0.82.

A more precise comparison is available in table 5. Table 5 reports comparison of models on some measures that clearly exhibit abilities to accommodate the set of anomaly long-short return differences: average absolute alpha, average absolute t-statistics of alpha, the number of anomalies for which the model produces the lowest absolute alpha among the four models being compared, and the Gibbons, Ross, and Shanken (1989) “GRS” test of whether all alphas equal zero. Panel A shows these measures for the set of 3 anomalies in TOTAL and KOSPI market, and 6 anomalies in KOSDAQ market that are explored above. In the first column, the values correspond to a zero-factor model, alphas equal to average excess returns. Model q-4 demonstrate the most explanatory power in capturing the set of anomalies over other models in TOTAL and KOSDAQ market, and model M-3 has a leading edge in KOSPI market. Because the performance of FF-3 is dominated by FF-5 in all three markets, and I compare FF-5 to other q-4 and M-3, and the direct comparison of FF-3 to them will be omitted here.

First, take a look at results in TOTAL market. Model q-4 gives average absolute alpha of 0.753%, followed by the value of 0.754% for M-3 on the same measure, and FF-5 provides approximately 1.8 times larger value of 1.361% than q-

4 does. The average absolute t-statistics shows a similar pattern. That is, q-4 has the average of 1.42, whereas M-3 and FF-5 yield the value of 1.59 and 3.047. For two anomalies, M-3 takes the absolute minimum alpha, and one anomaly for q-4. When comparing the p-values resulted from the GRS tests, q-4 shows the most ability accommodating three anomalies. None of the models succeed in capturing all three anomalies, and for q-4 the GRS_3 test produces a p-value of 0.029, compared to the value of 0.016 and 0.0000154 for M-3 and FF-5.

[INSERT TABLE 5 HERE]

In KOSPI market, the rankings of the top two models become reversed. M-3 is the best model in accommodating three anomalies, and q-4 takes the next place on that criterion. The average absolute alpha for M-3 is 0.406, whereas for q-4 the value is 0.777, and for FF-5 it is 2.03 in KOSPI market. A similar pattern is observed with the average absolute t-statistics as well. The GRS test proves that model M-3 shows an outstanding performance in accommodating three anomalies compared to other alternative models. For instance, the GRS test for M-3 produces the p-value of 0.454, meaning that the test fails to reject the hypothesis that all three anomalies are accommodated by the mispricing factor model. On the contrary, the GRS test for q-4 and FF-5 produces the p-value of 0.051 and 0.0000047.

Lastly, in KOSDAQ market, q-4 again takes the greatest ability in explaining six anomalies used in the mispricing factor. It is noticeable that q-4 actually yields higher average absolute alpha of 1.366 and average absolute t-statistics of 1.963 than does M-3 with the corresponding alpha and t-statistics of 0.932 and 1.818. In addition, for four anomalies, model M-3 attains the lowest absolute alpha and two anomalies for q-4. However, the GRS test for q-4 produces 0.0000117 and for M-3 it gives 0.0000105. This may mean that M-3 fails to capture one or two particular anomalies in a large degree worse than does the q-4.

In order to enhance the power of verification of the comparison in Korean stock market, apart from 3 and 6 anomalies examined above, I add 11 additional anomalies. The first five are explored by Stambaugh, Yu, and Yuan (2012) but not used in constructing the mispricing factor model in this paper. The rest of 6 anomalies are anomalies prevailing in Korean stock market. One of them is book-to-market value, which is the anomaly prevailing in Korean stock market. In addition, Lee (2016) find that five anomalies are not explained by the three-factor model of Fama and French (1993) in the cross section for the sample period from January 2001 to December 2014. The supplemented anomalies are briefly described in the Appendix; net stock issues, net operating assets, asset growth, investment-to-assets, and momentum from Stambaugh, Yu and Yuan (2012), book-to-market value, cash flow-to-price, dividend yield, operating accruals, taxable income-to-book income, and maximum daily returns.

Panel B of Table 5 reports the same measures as Panel A but for the larger set of 17 anomalies. (In TOTAL and KOSPI market, I supplement 3 anomalies not used in constructing the mispricing factor but used in KOSDAQ market, and thus in total 17 anomalies are employed in all the three markets.) In TOTAL market, the results are somewhat strange. FF-5 yields the smallest average absolute alpha of

0.556%, followed by the value of 0.56% for M-3, 0.684% for FF-3, and 0.794% for q-4 on the same measure. In terms of average absolute t-statistics, M-3 gives the smallest value, and the following FF-5, FF-3, and q-4 in order provides the larger value. For seven of the anomalies, model M-3 has the lowest absolute alpha, four anomalies for model FF-3, three anomalies for model FF-5, and one anomaly for model q-4. The GRS tests of whether all alphas equal zero with the p-values delivers the value of 0.008 for q-4, the half of the value for M-3, 0.003 for FF-5, and 0.001 for FF-3. With all the evidence I earn here, I can reach the conclusion that some anomalies are not captured by FF-3, FF-5, and M-3 in a great extent, and q-4 explains that anomalies at least better than the others. Finally, model q-4 is the best performing when it comes to explaining anomalies in TOTAL market.

In KOSPI market, the relative performance of the models is similar as in the analysis in Panel A: model M-3 shows the best performance, and q-4, FF-5, and FF-3 takes the next place in order. The smallest average absolute alpha of 0.493% and the smallest average absolute t-statistics of 0.916 are obtained by M-3. The mispricing factor model produces the lowest absolute alphas for five of anomalies, compared to four anomalies for FF-5 and FF-3, and three anomalies for q-4. Model M-3 also beats the alternative models in the GRS test. For the test with the 17 anomalies, the GRS test yields p-value for model M-3 of 0.215. The value states that the test does not reject the hypothesis that all 17 anomalies are accommodated by the mispricing factor model. On the contrary, the test gives p-value for q-4, the next best performing model, of 0.028

In KOSDAQ market, model M-3 performs worst in accommodating all 17 anomalies. Model q-4 has a leading performance, followed by FF-5 and FF-3 in order.

Model q-4 achieves the smallest average alpha of 1.11%, compared to values of 1.154%, 1.185%, and 1.471% for FF-5, M-3, and q-4. Model q-4 also has the smallest average absolute t-statistics of 1.594. Model M-3 takes the second place on this measure with the value of 2.047, followed by 2.082 and 2.369 for FF-5 and FF-3. For five of anomalies, M-3 has the lowest absolute alphas, compared to four anomalies for q-4, three anomalies for FF-5, and two anomalies for FF-3. The GRS test delivers p-values for model q-4 of 1.3E-07, for model FF-5 of 5.6E-12, for model FF-3 of 1.8E-13, and for model M-3 of 1.6E-14. Even though model M-3 has the smaller average absolute alpha and the average absolute t-statistics than FF-3, it earns the smaller GRS p-value than FF-3. The results hint that the mispricing factor lose their explanatory power in some particular anomalies but those are more explained by FF-3.

To sum up, the mispricing factor model has the superior ability in accommodating a large set of anomalies in KOSPI market, and the four-factor model of Hou, Xue, and Zhang (2015a) does in TOTAL and KOSDAQ market.

5.2 Comparing models' abilities to explain each other's factors

Next, I conduct pairwise model comparisons that evaluate each model's ability to price factors present in another. Panel A of Table 6 reports the alphas and corresponding t-statistics for (i) the FF-5 factors HML (book-to-market), RMW (profitability), and CMA (investment), (ii) the q-factors I/A (investment) and ROE (profitability), and (iii) the M-3 factor UMO. Panel B reports the GRS statistic and p-value testing whether all of the alphas with regard to an alternative model jointly equal zero.

In TOTAL market, model FF-5 shows the inferior ability in explaining each other's factors to q-4 and M-3. The model FF-5 has no power in pricing factors of q-4. It is somewhat astonishing that model FF-5 cannot capture the factors of q-4, given that model FF-5 has a different version of investment and profitability factor. The FF-5 alphas for I/A and ROE are 0.397% and 1.710%, with t-statistics of 3.38 and 7.6; the GRS p-value is 0.025 for the test of whether all two q-4 alphas for I/A and ROE are equal zero. Model FF-5 also fails to price the factor of M-3. The FF-5 alpha for UMO is 0.856%, with t-statistics of 3.03; the GRS p-value for the test is 0.005.

[INSERT TABLE 6 HERE]

The q-4 model fails to price the HML and RMW factor of FF-5. The q-4 alphas for those two factors are 0.853% and -0.488% and its t-statistics are 2.97 and -2.26. The fact that model q-4 cannot price RMW is a bit bizarre phenomenon as well in the above. The M-3 model succeeds in pricing RMW and CMA, yet it fails to price HML. The M-3 alpha for the factor is 0.816% and its t-statistic is 2.94. In comparison with the GRS p-value for the q-4 alpha and M-3 alpha for the three FF-5 factors, 0.016 and 0.025, the model M-3 is slightly better than q-4 in pricing the factors of FF-5.

Model q-4 can price UMO factor of M-3, with its alpha for UMO of 0.0426% and its corresponding t-statistic of 0.13. The GRS p-value for the test is 0.904, meaning model q-4 can strongly price the mispricing factor. On the other hand, M-

3 fails to price I/A and ROE factors from q-4, with its alphas for the two factors of 0.554% and 1.77%, and its corresponding t-statistics of 2.76 and 8.5. The GRS p-value for the joint test is 6.28E-13. In conclusion, model q-4 subsume the mispricing factor.

In KOSPI market, model FF-5 has the poorest ability in the comparison as the above. Although model FF-5 succeeds in explaining I/A factor of model q-4, it fails to capture ROE of model q-4 and UMO of model M-3. The GRS test p-value for FF-5 alphas for the two q-4 factors and the mispricing factor are 3.68E-11 and 3.1E-08. Model q-4 fails to price the FF-5 three factors. Those factors provide the q-4 alphas of less than 0.759% in absolute magnitude, with t-statistics of less than 2.59 in magnitude. The GRS test p-value for the q-4 alpha for the three FF-5 factors is 0.005. Model M-3 also does not price HML and CMA factor of FF-5. Its pricing ability for HML is better than q-4 but for CMA of FF-5 is worse than q-4: The M-3 alpha with HML is 0627% with t-statistic of 2.13 and CMA is 0.6% with t-statistic of 2.59. The GRS test p-value for the M-3 alpha for the three FF-5 factors is 0.022. Here again, model M-3 has a slightly better ability than q-4 in pricing the factors of FF-5.

Compared to model q-4 in its ability to explain each other's factors excluding FF-5 factors, M-3 is behind the race. The q-4 alpha for UMO is 1.019% with t-statistic of 2.35, whereas M-3 alphas for I/A and ROE are 0.684% and 1.383% with t-statistics of 2.96 and 5.86. The result becomes more obvious in the GRS test. The GRS test p-value for the q-4 alpha for UMO of 0.009 is much greater than the p-value for the M-3 alpha for the two q-4 factors of 1.07E-07.

In KOSDAQ market, a similar pattern is observed as in other markets that FF-5 has the third rank in pricing abilities to explain each other's factors and that the explanatory ability of model q-4 for UMO of M-3 is better than that of model M-3 for the two q-4 factors. One distinct point from TOTAL and KOSPI market is that model q-4 also prices the three FF-5 factors better than model M-3 does.

To conclude, the results show that the model FF-5 generally displays an inferior ability in explaining each other's factors to q-4 and M-3 in all the three markets. In comparing model q-4 and M-3 in terms of pricing abilities, the model M-3 is slightly better than q-4 in pricing the factor of FF-5. Yet, when it comes to horse race for the two models, the model q-4 has an edge over M-3 in that it accommodates the UMO factor of M-3 in TOTAL market, and it shows a greater performance in pricing the mispricing factor in KOSPI and KOSDAQ market, while model M-3 fails to price the two q-4 factors in all three markets.

5.3 Robustness

I use breakpoints of 20th and 80th percentiles rather than the conventional 30th and 70th as in Fama and French (1993, 2015) and Hou, Xue, and Zhang (2015a) in constructing the UMO and size factor in the mispricing factor model. As noted earlier, the reason for the alteration is that extremes of the mispricing measure best identify mispricing. I check whether the conclusion I reach in the above remain unchanged with 30th and 70th percentiles.

Table 7 and table 8 using the 30th and 70th breakpoints report the same empirical analysis as in table 5 and table 6. The overall conclusion is the same as the above. Model M-3 still has the best performance in accommodating a large set of anomalies in KOSPI market, and model q-4 does in TOTAL and KOSDAQ market.

One different point is that model M-3 becomes the second-best performing model in explaining the set of 17 anomalies in KOSDAQ market using 30th and 70th breakpoints as seen in Panel B of Table 7, but it obtains the fourth rank in that analysis when using 20th and 80th percentiles. Additionally, model q-4 remain its edge over M-3 in pricing each other's factors. Model FF-5 shows the least ability in explaining anomalies and price alternative models' factors compared to q-4 and M-3.

[INSERT TABLE 7 HERE]

[INSERT TABLE 8 HERE]

6. Conclusions

A conventional way of constructing a factor is by taking the information on one anomaly using 2 x 3 sorts with size and the anomaly. I take a different approach that combines information from multiple anomalies and develops one mispricing factor from it as Stambaugh and Yuan (2017) do. I use 3 anomalies in TOTAL and KOSPI market, and 6 anomalies in constructing the mispricing factor.

Given that investor sentiment is a systematic component of mispricing, the motivation of forming a mispricing factor comes from the two main aspects: (1) anomalies partly reflect mispricing and possess common investor sentiment effects and (2) the existence of arbitrate asymmetry prevents the correction of mispricing.

Hence, the overpriced (short-leg) stocks are more likely exhibit greater sensitivity than underpriced (long-leg) stocks, and the long-short spreads captures investor sentiment. Yet, one month lagged investor sentiment index has no impact on the mispricing factor in Korean stock market. The reason for the phenomenon might be the insufficient transaction volume and trading value of short-selling in Korean stock market.

Along with the mispricing factor, I add market and size factor to introduce a three-factor model. I find that the three-factor model's ability to accommodate a range of anomalies outperform that of both the five-factor model of Fama and French (2015) and the four-factor model of Hou, Xue, and Zhang (2015a) in KOSPI market. Yet, the four-factor model of Hou, Xue, and Zhang (2015a) takes the first place in explaining a set of anomalies in TOTAL and KOSDAQ market. When comparing models' abilities to price each other's factors, the four-factor model of Hou, Xue, and Zhang (2015a) performs best, followed by the mispricing factor model and the five-factor model of Fama and French (2015) in order.

Appendix

The 6 anomalies Used to Construct the Mispricing Factor

Below I specify the construction of the anomaly measure used to construct mispricing scores and form anomaly portfolios and mispricing factors. The anomaly measures for each stock are computed at the end of each month. I exclude stocks worth less than ₩1,000, avoid microstructure effects, and use common shares. I also eliminate stocks with return values missing and with annual (or quarterly) asset and sales values zero or missing. I include only a stock having non-missing values at the end of month t-1 for at least two of the three anomalies in computing UMO in TOTAL and KOSPI market, and at least four of the six anomalies in KOSDAQ market.

1. Composite equity issues by Daniel and Titman (2006) used in KOSDAQ market

   Composite equity issues$_{i,t}$ (CEI) = $(MG_{t-12}+MG_{t-11}+\ldots+MG_{t-1}) - (R_{i,t-12}+R_{i,t-11}+\ldots R_{i,t-1})$ where MG = the growth in equity market capitalization and R = stock returns.

   I lag the quantity four months to make its timing more coincident with the measure of net stock issues, which will be introduced below. At the beginning of each month t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on CEI in month t-1. Monthly value-weighted decile returns are calculated, and the deciles are rebalanced on a monthly basis.

2. Accruals by Sloan (1996) used in KOSDAQ market

$\text{Accruals}_{i,t} = \frac{(NCWC - Dep - Amor)_{i,t} - (NCWC - Dep - Amor)_{i,t-1}}{AVGAT_{i,t-1}}$ where NCWC = noncash working capital, DEP = depreciation expense, AMOR = amortization expense, and $AVGAT_{i,t-1} = (AT_{i,t-1}+AT_{i,t-2}/2)$.

Noncash working capital = Δ current assets – Δ cash and short-term investment – Δ current liabilities + Δ debt included in current liabilities + Δ income taxes payable.

At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on Accruals at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

3. Distress probability (HAZARD rate) by Lee and Kim (2015)

HAZARD = -3.83 - 1.58*NIMTA + 2.07*TLMTA - 2.11*EXRETAVG - 0.02*RSIZE + 1.36*SIGMA - 1.51*CASHMTA - 0.52PRICE - 0.45*SLMTA - 3.7*FFOMTA

where NIMTA = quarterly net income divided by firm scale, where the latter is computed as the sum of total liabilities and market equity capitalization, TLMTA = total liabilities divided by firm scale, EXRETAVG = $\frac{1-\Phi}{1-\Phi^{12}}(EXRET_{t-1}+\ldots\ldots\Phi^{11}EXRET_{t-12})$ $\Phi = 2^{-1/3}$, EXRET = the stock's monthly log return in months minus the log return on the KOSPI (KOSDAQ) index, Rsize = the log of the ratio of the stock's market capitalization to that of the KOSPI (KOSDAQ) index, SIGMA = the stock's daily standard deviation for the most recent three months, expressed on an annualized basis, CASHMTA = cash and short-term investment divided by firm scale, PRICE = the log of the share price, truncated above at 15. If stock price is less than ₩15,000 then the value would be share price divided by 1000. EXRETAVG, SIGMA, RSIZE and PRICE are for month t-1. SLMTA = sales divided by firm scale, and FFOMTA = cash flow from operating divided by firm scale.

At the beginning of each month t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on HAZARD in month t-1. Monthly value-weighted decile returns are calculated, and the deciles are rebalanced on a monthly basis.

4. Bankruptcy probability (Logit model) by Lee and Kim (2015)

   LOGIT = 2.38 + 4.89*TLTA - 0.39lnTA - 0.15*RETA - 2.74CASHTA - 3.32*FFOTA - 0.83*lnSLTA

   where TLTA = the book value of debt divided by total assets, lnTA = the log of total assets, RETA = retained earnings divided by total assets, CASHTA = the cash divided by total assets, FFOTA = cash flow from operating divided by total assets, and lnSLTA = the log of the ratio of sales to the total assets.

   At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on LOGIT at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

5. Gross profitability premium by Wang and Yu (2013) used in KOSDAQ market

   Gross profitability premium$_{i,t}$ (GPP) = $\frac{REV_{i,t} - COGS_{i,t}}{AT_{i,t}}$ where REV = the toal revenue, COGS = cost of goods sold, and AT = total assets.

At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on GPP at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

6. Return on assets by Wang and Yu (2013)

   $ROA_{i,q} = \frac{EBITQ_{i,q}}{ATQ_{i,q-1}}$ where EBITQ = quarterly earnings before interest and taxes and ATQ = quarterly total assets.

   At the end of each quarter, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on ROA at the end of previous quarter. Monthly value-weighted decile returns are calculated, and the deciles are rebalanced at the end of each quarter.

11 Additional Anomalies Used in Producing Table 5

First 5 anomalies used in Stambaugh and Yu, and Yuan (2012) but not in this paper

1. Net stock issues by Ritter (1991)

   Net stock $issue_{i,t}$ (NSI) = log (split-adjusted $shares_{i,t}$/split-adjusted $shares_{i,t-1}$) where Split-adjusted shares = shares outstanding times the adjustment factor that reflecting stock dividends and all stock splits.

   At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on NSI at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

2. Net operating assets by Hirshleifer, Hou, Teoh, and Zhang (2004)

   Net operating assets$_{i,t}$ (NOA) = $\frac{OAi,t-OLi,t}{ATi,t-1}$ where $OA_{i,t}$ = operating assets, $OL_{i,t}$ = operating liabilities, and $AT_{i,t}$ = total assets.

   Operating assets = total assets - cash and short-term investment

   Operating liabilities = total assets - debt included in current liabilities - long-term debt - common equity - minority interests - preferred stocks (the last two items are zero if missing)

   At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on NOA at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

3. Asset growth by Cooper, Gulen, and Schill (2008)

   Asset growth$_{i,t}$ (AG) = $\frac{ATi,t-ATi,t-1}{ATi,t-1}$ where AT = total assets.

   At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on AG at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

4. Investment-to-assets by Titman, Wei, and Xie (2004)

Investment-to-assets$_{i,t}$ (IA) = $\frac{(PPE+Inv)i,t-(PPE+Inv)i,t-1}{ATi,t}$ where PPE = property, plant, and equipment, Inv = inventories, and AT = total assets.

At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on IA at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

5. Momentum by Jegadeesh and Titman (1993)

   Momentum$_{i,t}$ (MOM) = $R_{i,t-12}$+$R_{i,t-11}$+….$R_{i,t-2}$ where R = stock returns.

   At the beginning of each month t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on MOM in month t-1. Monthly value-weighted decile returns are calculated, and the deciles are rebalanced on a monthly basis.

Next 6 anomalies present in Korean stock market

6. Book-to-market equity (B/M) by Rosenberg, Reid, and Lanstein (1985)

   B/M$_{i,t}$ = $\frac{BEi,t}{M\,Ei,t}$ where BE = the total equity minus preferred stock equity, and ME = stock price times the number of common shares

   At the end of June of each year t, I split stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on B/M at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

7. Cash flow-to-price (CF/P) by Lakonishok, Shleifer, and Vishny (1994)

$CF/P_{,t} = \frac{CFi,t}{M\,Ei,t}$ where CF = the difference in cash flow in the statement of cash flow, and ME = stock price times the number of common shares.

At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on CF/P at the end of December of t-1. I exclude firms with negative CFs. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

8. Dividend yield (D/P) by Litzenberger and Ramaswamy (1979)

$D/P_{,t} = \frac{Divi\,,t}{M\,Ei,t}$ where Div = the dividends paid in the statement of cash flow, and ME = stock price times the number of common shares.

I make an adjustment that I replace dividends yield with dividends because monthly dividends are not available due to data limitation. At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on D/P at the end of December of t-1. I exclude firms with not paying dividends. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

9. Operating accruals (OA) by Hribar and Collins (2002)

$OA_t = \frac{OAi,t}{ATi,t-1}$ where OA = net income minus cash flow from operations in the statement of cash flow, and AT = total assets.

At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on OA at the end of December of t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

10. Taxable income-to-book income (TI/BI) by Green, Hand, and Zhang (2013)

$TI/BI_t = \frac{TI_{i,t}}{NI_{i,t}}$ where TI = pretax income, and NI = net income.

At the end of June of each year t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting), based on TI/BI at the end of December t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t+1, and the deciles are rebalanced in June of t+1.

11. Maximum daily return (MDR) by Bali, Cakici, and Whitelaw (2011)

At the beginning of each month t, I sort stocks into deciles (KOSPI breakpoints used in case of TOTAL market in sorting) based on the maximum daily return (MDR) in month t-1. I exclude firms with having less than 15 daily returns. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month t+1.

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Figure 1

The investor sentiment index

The investor sentiment index from 1999:01 to 2010:12. They sentiment index is the first principal component of six measure: the monthly trading imbalance of individual investors, the monthly stock fund flow ratio, the Customer Expectation Index for the business cycle, customers' deposits for stock investment, the turnover ratio in the Korea Exchange, and the equity share in new issues. To control for the business cycle, the six raw sentiment measures are regressed on the growth of the industrial production index, the durable sales index, the semi-durables sales index, the non-durable sales index, the service production index, and the coincident composite index for business cycle change.

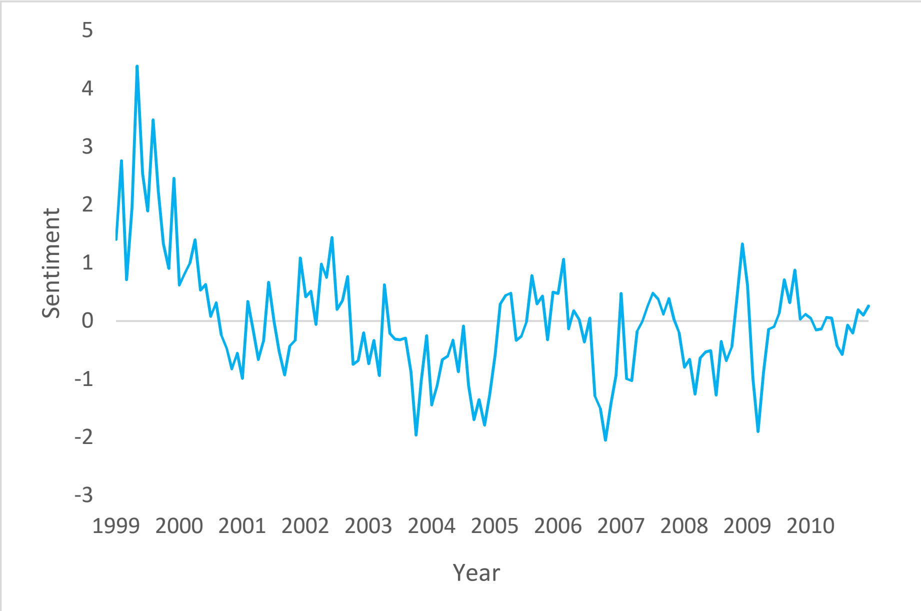

Table 1

Summary Statistics

The table reports summary statistics for the monthly observations of the factors in the M-3 model in TOTAL, KOSPI, and KOSDAQ market in a row. MKT_total, MKT_kospi, and MKT_kosdaq denotes the market return of TOTAL, KOSPI and KOSDAQ, respectively. The sample period is from August 2001 to December 2016 (185 months).

			Correlations		
Factor	Mean (%)	Std. Dev. (%)	MKT_total	SMB	UMO
MKT_total	-0.15	5.83	1.00		
SMB	-1.64	4.13	-0.28	1.00	
UMO	2.10	6.41	-0.31	-0.34	1.00

			Correlations		
Factor	Mean (%)	Std. Dev. (%)	MKT_kospi	SMB	UMO
MKT_kospi	0.42	5.91	1.00		
SMB	-1.17	4.54	-0.33	1.00	
UMO	2.30	6.41	-0.38	-0.09	1.00

			Correlations		
Factor	Mean (%)	Std. Dev. (%)	MKT_kosdaq	SMB	UMO
MKT_kosdaq	-0.34	7.63	1.00		
SMB	-1.73	4.37	-0.38	1.00	
UMO	2.56	5.08	-0.42	-0.04	1.00

Table 2

Factor Loadings and Alphas of Anomaly Strategies Under the Mispricing-Factor Model

The table reports the model's factor loadings and monthly alphas (in percent) for 3 anomalies for TOTAL and KOSPI market and 6 anomalies for KOSDAQ market. For each anomaly, the regression estimated is

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{UMO}UMO_t + \varepsilon_t,$$

where R_t is the return in month t on the anomaly's long-leg, short-leg, or long-short spread, MKT_t, is the excess market return, SMB_t is the model's size factor, and UMO_t is the mispricing factor. The long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg holds the stocks in the highest decile, where a high value of the measure is associated with lower return. In case of TOTAL market, the breakpoints are based on KOSPI deciles. Stocks worth less than ₩1,000 are deleted. In addition, stocks with return values missing and with annual (or quarterly) asset and sales values zero or missing are removed. The sample period is from August 2001 to December 2016 (185 months). The t-statistics are shown in parentheses and all t-statistics are based on the heteroscedasticity-consistent standard errors of White (1980).

Anomaly	α		MKT_total		SMB		UMO	
Panel A: Long-Short Spreads								
Failure probability	0.591	(0.90)	-0.311***	(-2.99)	0.147	(0.92)	0.928***	(7.11)
Bankruptcy probability	-0.266	(-0.78)	-0.130*	(-1.76)	-0.624***	(-7.39)	0.708***	(11.06)
Return on assets	1.404***	(3.09)	-0.0941	(-1.07)	0.0943	(0.82)	0.740***	(7.35)
Panel B: Long Legs								
Failure probability	0.372	(1.30)	0.748***	(13.08)	0.149*	(1.93)	0.192***	(3.89)
Bankruptcy probability	0.330***	(3.29)	0.969***	(37.88)	0.0191	(0.67)	0.146***	(7.14)
Return on assets	0.627***	(2.80)	1.030***	(22.06)	0.0833	(1.38)	0.124***	(3.32)
Panel C: Short Legs								
Failure probability	-0.219	(-0.40)	1.059***	(12.35)	0.00213	(0.01)	-0.736***	(-6.28)

Bankruptcy probability	0.596**	(1.97)	1.099***	(16.60)	0.643***	(8.17)	-0.562***	(-9.50)
Return on assets	-0.777**	(-2.08)	1.124***	(15.36)	-0.0110	(-0.11)	-0.616***	(-7.16)

Anomaly	α		MKT_kospi		SMB		UMO	
Panel A: Long-Short Spreads								
Failure probability	0.202	(0.25)	-0.333**	(-2.22)	0.0387	(0.25)	1.006***	(6.31)
Bankruptcy probability	-0.0767	(-0.17)	-0.163*	(-1.74)	-0.656***	(-5.87)	0.704***	(7.76)
return on assets	0.939*	(1.76)	-0.144	(-1.08)	0.149	(1.08)	0.714***	(6.19)
Panel B: Long Legs								
Failure probability	-0.246	(-0.83)	0.763***	(13.99)	0.122*	(1.89)	0.231***	(4.84)
Bankruptcy probability	-0.194*	(-1.70)	0.953***	(31.61)	0.00769	(0.24)	0.122***	(5.71)
return on assets	0.0924	(0.41)	0.994***	(18.74)	0.101*	(1.90)	0.116***	(3.19)
Panel C: Short Legs								
Failure probability	-0.448	(-0.63)	1.096***	(7.92)	0.0829	(0.56)	-0.774***	(-5.13)
Bankruptcy probability	-0.117	(-0.28)	1.116***	(11.93)	0.663***	(6.00)	-0.583***	(-6.83)
return on assets	-0.846*	(-1.69)	1.139***	(8.91)	-0.0484	(-0.39)	-0.598***	(-5.44)

Anomaly	α		MKT_kosdaq		SMB		UMO	
Panel A: Long-Short Spreads								
Composite equity issues	1.730***	(3.20)	-0.00849	(-0.12)	0.00723	(0.06)	0.361***	(3.93)
Accruals	0.769	(1.23)	0.133	(1.55)	0.151	(0.76)	0.175	(1.47)
Failure probability	0.381	(0.59)	-0.258***	(-3.24)	-0.211	(-1.44)	0.913***	(8.12)
Bankruptcy probability	-1.388***	(-3.06)	0.00141	(0.02)	-0.278**	(-1.99)	0.974***	(10.52)
Gross profitability premium	-1.051**	(-2.33)	-0.0406	(-0.57)	-0.169	(-1.33)	0.848***	(8.19)
return on assets	0.274	(0.50)	-0.0289	(-0.45)	-0.467***	(-3.87)	1.026***	(11.15)
Panel B: Long Legs								
Composite equity issues	0.0672	(0.21)	1.006***	(25.11)	0.0655	(0.92)	0.0905	(1.39)
Accruals	-0.445	(-0.96)	1.188***	(20.96)	0.0312	(0.29)	-0.0228	(-0.30)
Investment to assets	-0.163	(-0.33)	0.982***	(20.50)	0.161*	(1.71)	-0.319***	(-4.22)
Failure probability	-0.483	(-1.23)	0.852***	(13.95)	-0.0374	(-0.40)	0.255***	(3.05)
Bankruptcy probability	-1.153***	(-4.28)	0.986***	(21.13)	-0.100	(-1.60)	0.312***	(5.00)
Gross profitability premium	-1.316***	(-4.02)	0.975***	(17.64)	0.00530	(0.07)	0.363***	(5.20)

return on assets	-0.767**	(-2.59)	1.102***	(25.07)	-0.169**	(-2.34)	0.384***	(6.22)
Panel C: Short Legs								
Composite equity issues	-1.662***	(-3.69)	1.015***	(16.19)	0.0583	(0.59)	-0.271***	(-3.24)
Accruals	-1.214***	(-3.01)	1.055***	(18.73)	-0.120	(-0.97)	-0.198**	(-2.29)
Failure probability	-0.864	(-1.54)	1.110***	(17.21)	0.173	(1.27)	-0.657***	(-8.12)
Bankruptcy probability	0.235	(0.61)	0.985***	(17.03)	0.178	(1.48)	-0.662***	(-8.62)
Gross profitability premium	-0.265	(-0.86)	1.016***	(22.18)	0.174*	(1.97)	-0.486***	(-6.63)
return on assets	-1.040**	(-2.49)	1.131***	(21.18)	0.297***	(3.56)	-0.642***	(-8.23)

Table 3

Investor Sentiment and the Factors

The table reports estimates of b in the regression

$$R_t=a+bS_{t-1}+u_t,$$

where R_t is the excess return in month t on either the long leg, the short leg, or the long-short spread for each of the factors (MKT, SMB, and UMO), and S_{t-1} is the previous month's level of investor-sentiment index of Baker and Wurgler (2006). The sample period is from August 2001 to December 2010 (113 months). The t-statistics are shown in parentheses and all t-statistics are based on the heteroscedasticity-consistent standard errors of White (1980).

Factor	Long Leg		Short Leg		Long-Short	
	$\hat{b}$	t-stat	$\hat{b}$	t-stat	$\hat{b}$	t-stat
MKT_total					-0.719	(-0.96)
SMB	-1.470	(-1.37)	-0.669	(-0.65)	-0.800	(-1.51)
UMO	-0.952	(-1.34)	-1.090	(-0.73)	0.137	(0.14)

Factor	Long Leg		Short Leg		Long-Short	
	$\hat{b}$	t-stat	$\hat{b}$	t-stat	$\hat{b}$	t-stat
MKT_kospi					-0.728	(-0.96)
SMB	-1.352	(-1.46)	-0.719	(-0.75)	-0.633	(-1.17)
UMO	-0.807	(-1.25)	-0.699	(-0.49)	-0.108	(-0.11)

Factor	Long Leg		Short Leg		Long-Short	
	$\hat{b}$	t-stat	$\hat{b}$	t-stat	$\hat{b}$	t-stat
MKT_kosdaq					-0.706	(-0.63)
SMB	-1.509	(-1.34)	-0.905	(-0.72)	-0.604	(-1.09)
UMO	-0.971	(-0.96)	-1.169	(-0.75)	0.198	(0.24)

Table 4

Anomaly Alphas Under Different Factor Models

For long-short spreads corresponding to 3 anomalies in TOTAL and KOSPI market, and 6 anomalies in KOSDAQ markets, the table reports information about alphas computed under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the three-factor mispricing-factor model introduced in this study, denoted M-3. The average unadjusted long-short returns (the alphas in a model with no factors) are also reported. The long leg is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg is composed of stocks in the highest decile, where a high value of the measure is associated with lower return. In case of TOTAL market, the breakpoints are based on KOSPI deciles. Stocks worth less than ₩1,000 are deleted. In addition, stocks with return values missing and with annual (or quarterly) asset and sales values zero or missing are removed. The sample period is from August 2001 to December 2016 (185 months). The Panel A reports monthly alphas (in percent); panel B reports their heteroscedasticity-consistent t-statistics based on White (1980).

Anomaly	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: Alphas					
Failure probability (Hazard rate)	2.344	1.583**	1.209*	0.994	0.591
Bankruptcy probability (Logit)	2.264	1.380***	1.147***	1.099**	-0.266
Return on assets	2.816	2.176***	1.729***	-0.167	1.404***
Panel B: t-statistics					
Failure probability (Hazard rate)	3.3	(2.52)	(1.86)	(1.43)	(0.90)
Bankruptcy probability (Logit)	4.17	(3.94)	(3.34)	(2.44)	(-0.78)
Return on assets	5.15	(4.23)	(3.94)	(-0.39)	(3.09)

Anomaly	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: Alphas					
Failure probability (Hazard rate)	2.328	2.374***	1.981**	0.857	0.202
Bankruptcy probability (Logit)	2.242	2.099***	1.892***	1.396**	-0.077
return on assets	2.344	2.563***	2.218***	0.0782	0.939*
Panel B: t-statistics					
Failure probability (Hazard rate)	2.71	(2.98)	(2.50)	(1.00)	(0.25)
Bankruptcy probability (Logit)	3.7	(4.91)	(4.37)	(2.48)	(-0.17)
return on assets	3.61	(4.05)	(4.06)	(0.14)	(1.76)

Anomaly	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: Alphas					
Composite equity issues	2.643	2.160***	1.902***	1.858***	1.730***
Accruals	0.911	1.399**	1.337**	1.001	0.769
Failure probability (Hazard rate)	3.164	2.730***	2.415***	2.346***	0.381
Bankruptcy probability (Logit)	1.582	1.921***	1.014**	0.537	-1.388***
Gross profitability premium	1.422	1.983***	0.937	0.574	-1.051**
return on assets	3.711	4.434***	3.629***	1.878***	0.274
Panel B: t-statistics					
Composite equity issues	6.1	(4.59)	-4.17	(3.39)	(3.20)
Accruals	1.75	(2.30)	(2.29)	(1.39)	(1.23)
Failure probability (Hazard rate)	4.86	(4.37)	(4.01)	(2.67)	(0.59)
Bankruptcy probability (Logit)	2.87	(3.34)	(2.05)	(0.79)	(-3.06)
Gross profitability premium	2.74	(3.30)	(1.65)	(0.82)	(-2.33)
return on assets	6.24	(7.54)	(6.64)	(2.72)	(0.50)

Table 5

Summary Measures of Models' Abilities in Explain Anomalies

The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the three-factor mispricing-factor model introduced in this study, denoted M-3. The average unadjusted long-short returns (the alphas in a model with no factors) are also reported. For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibborns, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, GRS_3 tests whether the three alphas for the full-sample anomalies equal zero in TOTAL and KOSPI market, while GRS_6 uses six anomalies in KOSDAQ market. In Panel B, GRS_{17} tests whether the 17 alphas for the full-sample anomalies equal zero. The sample period is from August 2001 to December 2016 (185 months).

Measure	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: 3 anomalies					
Average $\lvert\alpha\rvert$	2.475	1.713	1.361	0.753	0.754
Average $\lvert t\rvert$	4.207	3.563	3.047	1.420	1.590
GRS_3	9.754	9.490	8.928	3.064	3.544
p3	5.4E-06	7.5E-06	1.5E-05	0.029	0.016
Number of min $\lvert\alpha\rvert$	0	0	0	1	2
Panel B: 17 anomalies					
Average $\lvert\alpha\rvert$	1.119	0.684	0.556	0.794	0.560
Average $\lvert t\rvert$	2.149	1.448	1.222	1.479	1.165
GRS_{17}	3.599	2.544	2.389	2.120	2.295
$p17$	8.6E-06	0.001	0.003	0.008	0.004
Number of min $\lvert\alpha\rvert$	2	4	3	1	7

Measure	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: 3 anomalies					
Average $\lvert\alpha\rvert$	2.305	2.345	2.030	0.777	0.406
Average $\lvert t\rvert$	3.340	3.980	3.643	1.207	0.727
GRS_3	6.402	10.990	9.872	2.637	0.877
p3	3.8E-04	1.2E-06	4.7E-06	0.051	0.454
Number of min $\lvert\alpha\rvert$	0	0	0	1	2
Panel B: 17 anomalies					
Average $\lvert\alpha\rvert$	0.978	0.864	0.741	0.757	0.493
Average $\lvert t\rvert$	1.642	1.559	1.366	1.289	0.916
GRS_{17}	2.748	2.595	2.482	1.831	1.274
$p17$	4.8E-04	0.001	0.002	0.028	0.215
Number of min $\lvert\alpha\rvert$	1	4	4	3	5

Measure	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: 6 anomalies					
Average $\lvert\alpha\rvert$	2.239	2.438	1.872	1.366	0.932
Average $\lvert t\rvert$	4.093	4.240	3.468	1.963	1.818
GRS_6	14.201	15.165	12.465	5.929	5.975
p6	3.4E-13	5.8E-14	1.2E-11	1.2E-05	1.1E-05
Number of min $\lvert\alpha\rvert$	0	0	0	2	4
Panel B: 17 anomalies					
Average $\lvert\alpha\rvert$	1.471	1.357	1.154	1.110	1.185
Average $\lvert t\rvert$	2.742	2.369	2.082	1.594	2.047
GRS_{17}	9.008	7.481	6.708	4.493	8.063
$p17$	2.2E-16	1.8E-13	5.6E-12	1.3E-07	1.6E-14
Number of min $\lvert\alpha\rvert$	3	2	3	4	5

Table 6

Abilities of Models FF-5, q-4, and M-3 to Explain Each Other's Factors

Panel A reports a factor's estimated monthly alpha (in percent) with respect to each of the other models (with White [1980] heteroscedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shaken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model (with p-values in parentheses). The factors whose alphas are tested are those other than a model's market and size factors. The models considered are the five-factor model of Fama and French (2015), which includes the factors *HML, RMW*, and *CMA*, denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), which includes the factors *I/A* and *ROE*, denoted q-4; and the three-factor mispricing-factor model, which includes the factor *UMO*, denoted M-3. The sample period is from August 2001 to December 2016 (185 months).

Factors	Alpha computed with respect to model		
	FF-5	q-4	M-3
Panel A: Alphas (t-statistics)			
Factors in FF-5			
HML	-	0.853***	0.816***
		(2.97)	(2.94)
RMW	-	-0.488**	-0.0415
		(-2.26)	(-0.18)
CMA	-	0.0561	0.169
		(0.41)	(0.83)
Factors in q-4			
I/A	0.397***	-	0.554***
	(3.38)		(2.76)
ROE	1.710***	-	1.770***
	(7.60)		(8.50)
Factors in M-3			
UMO	0.856***	0.0426	-
	(3.03)	(0.13)	-
Panel B: GRS F-statistic (p-value)			
HML, RMW, CMA	-	3.510	3.184
		(0.016)	(0.025)
I/A, ROE	30.165	-	32.976
	(5.23E-12)		(6.28E-13)
UMO	8.074	0.015	-
	(0.005)	(0.904)	

Factors	Alpha computed with respect to model		
	FF-5	q-4	M-3
Panel A: Alphas (t-statistics)			
Factors in FF-5			
HML	-	0.759**	0.627**
		(2.48)	(2.13)
RMW	-	-0.717***	-0.453
		(-2.96)	(-1.58)
CMA	-	0.295*	0.600**
		(1.86)	(2.59)
Factors in q-4			
I/A	0.126	-	0.684***
	(0.86)		(2.96)
ROE	1.730***	-	1.383***
	(7.36)		(5.86)
Factors in M-5			
UMO	1.866***	1.019**	-
	(5.82)	(2.35)	
Panel B: GRS F-statistic (p-value)			
HML, RMW, CMA	-	4.375	3.286
		(0.005)	(0.022)
I/A, ROE	27.580	-	17.575
	(3.68E-11)		(1.07E-07)
UMO	33.524	6.915	-
	(3.10E-08)	(0.009)	

Factors	Alpha computed with respect to model		
	FF-5	q-4	M-3
Panel A: Alphas (t-statistics)			
Factors in FF-5			
HML	-	1.448**	1.493***
		(2.41)	(3.61)
RMW	-	0.672	-0.472
		(1.23)	(-1.30)
CMA	-	0.258	0.714**
		(1.27)	(2.00)
Factors in q-4			
I/A	0.415**	-	0.931***
	(2.08)		(2.71)
ROE	3.040***	-	1.882***
	(7.63)		(4.63)
Factors in M-3			
UMO	1.893***	1.220***	-
	(5.72)	(2.80)	
Panel B: GRS F-statistic (p-value)			
HML, RMW, CMA	-	5.204	10.272
		(0.002)	(2.84E-06)

I/A, ROE	37.050	-	14.334
	(3.53E-14)		(1.67E-06)
UMO	35.645	10.899	-
	(1.24E-08)	(0.001)	

Table 7
Summary Measures of Models' Abilities in Explain Anomalies with 30th and 70th breakpoints

The table reports measures that summarize the degree to which anomalies produce alpha under four different factor models: the three-factor model of Fama and French (1993), denoted FF-3; the five-factor model of Fama and French (2015), denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), denoted q-4; and the three-factor mispricing-factor model introduced in this study, denoted M-3. The average unadjusted long-short returns (the alphas in a model with no factors) are also reported. For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibborns, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table. In Panel A, GRS_3 tests whether the three alphas for the full-sample anomalies equal zero in TOTAL and KOSPI market, while GRS_6 uses six anomalies in KOSDAQ market. In Panel B, GRS_{17} tests whether the 17 alphas for the full-sample anomalies equal zero. The sample period is from August 2001 to December 2016 (185 months). 30th and 70th breakpoints are used in constructing the mispricing factor and size factor in the M-3.

Measure	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: 3 anomalies					
Average $\lvert\alpha\rvert$	2.475	1.713	1.361	0.753	0.734
Average $\lvert t\rvert$	4.207	3.563	3.047	1.420	1.617
GRS_3	9.754	9.490	8.928	3.064	3.303
p3	5.35E-06	7.52E-06	1.54E-05	0.029	0.022
Number of min $\lvert\alpha\rvert$	0	0	0	1	2
Panel B: 17 anomalies					
Average $\lvert\alpha\rvert$	1.119	0.684	0.556	0.794	0.531
Average $\lvert t\rvert$	2.149	1.448	1.222	1.479	1.113
GRS_{17}	3.599	2.544	2.389	2.120	2.003
$p17$	0.00001	0.001	0.003	0.008	0.014
Number of min $\lvert\alpha\rvert$	2	4	4	1	5

Measure	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: 3 anomalies					
Average $\|\alpha\|$	2.305	2.345	2.030	0.777	0.493
Average $\|t\|$	3.340	3.980	3.643	1.207	0.923
GRS_3	6.402	10.990	9.872	2.637	0.877
p3	0.0004	0.0000	0.0000	0.051	0.511
Number of min $\|\alpha\|$	0	0	0	1	2
Panel B: 17 anomalies					
Average $\|\alpha\|$	0.978	0.864	0.741	0.757	0.546
Average $\|t\|$	1.642	1.559	1.366	1.289	1.026
GRS_{17}	2.748	2.595	2.482	1.831	1.275
$p17$	0.0005	0.0010	0.0017	0.028	0.215
Number of min $\|\alpha\|$	1	4	3	3	6

Measure	Unadjusted	FF-3	FF-5	q-4	M-3
Panel A: 3 anomalies					
Average $\|\alpha\|$	2.239	2.438	1.872	1.366	0.889
Average $\|t\|$	4.093	4.240	3.468	1.963	1.715
GRS_6	14.201	15.165	12.465	5.929	5.462
p6	3.42E-13	5.75E-14	1.15E-11	1.17E-05	3.31E-05
Number of min $\|\alpha\|$	0	0	0	2	4
Panel B: 17 anomalies					
Average $\|\alpha\|$	1.471	1.357	1.154	1.110	1.066
Average $\|t\|$	2.742	2.369	2.082	1.594	1.883
GRS_{17}	9.008	7.481	6.708	4.493	6.662
$p17$	2.22E-16	1.81E-13	5.56E-12	1.29E-07	6.27E-12
Number of min $\|\alpha\|$	3	2	3	4	5

Table 8

Abilities of Models FF-5, q-4, and M-3 to Explain Each Other's Factors with 30th and 70th breakpoints

Panel A reports a factor's estimated monthly alpha (in percent) with respect to each of the other models (with White [1980] heteroscedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shaken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model (with p-values in parentheses). The factors whose alphas are tested are those other than a model's market and size factors. The models considered are the five-factor model of Fama and French (2015), which includes the factors *HML, RMW*, and *CMA*, denoted FF-5; the four-factor model of Hou, Xue, and Zhang (2015a), which includes the factors *I/A* and *ROE*, denoted q-4; and the three-factor mispricing-factor model, which includes the factor *UMO*, denoted M-3. The sample period is from August 2001 to December 2016 (185 months). 30th and 70th breakpoints are used in constructing the mispricing factor and size factor in the M-3.

Factors	Alpha computed with respect to model		
	FF-5	q-4	M-3
Panel A: Alphas (t-statistics)			
Factors in FF-5			
HML	-	0.853***	0.728***
		(2.97)	(2.74)
RMW	-	-0.488**	-0.111
		(-2.26)	(-0.48)
CMA	-	0.0561	0.249
		(0.41)	(1.18)
Factors in q-4			
I/A	0.397***	-	0.602***
	(3.38)		(2.95)
ROE	1.710***	-	1.695***
	(7.60)		(8.39)
Factors in M-3			
UMO	0.840***	0.225	-
	(3.35)	(0.77)	-
Panel B: GRS F-statistic (p-value)			
HML, RMW, CMA	-	3.510	2.645
		(0.016)	(0.051)
I/A, ROE	30.165	-	30.773

	(5.23E-12)		(3.2E-12)
UMO	11.685	0.598	-
	(0.001)	(0.44)	

Factors	Alpha computed with respect to model		
	FF-5	q-4	M-5
Panel A: Alphas (t-statistics)			
Factors in FF-5			
HML	-	0.759**	0.737***
		(2.48)	(2.61)
RMW	-	-0.717***	-0.328
		(-2.96)	(-1.19)
CMA	-	0.295*	0.610***
		(1.86)	(2.70)
Factors in q-4			
I/A	0.126	-	0.633***
	(0.86)		(2.70)
ROE	1.730***	-	1.365***
	(7.36)		(6.06)
Factors in M-5			
UMO	1.386***	0.527*	-
	(5.05)	(1.68)	
Panel B: GRS F-statistic (p-value)			
HML, RMW, CMA	-	4.375	3.736
		(0.01)	(0.01)
I/A, ROE	27.580	-	18.220
	(3.68E-11)		(6.22E-08)
UMO	25.437	3.079	-
	(1.12E-06)	(0.08)	

Factors	Alpha computed with respect to model		
	FF-5	q-4	M-3
Panel A: Alphas (t-statistics)			
Factors in FF-5			
HML	-	1.448**	1.372***
		(2.41)	(3.24)
RMW	-	0.672	-0.451
		(1.23)	(-1.24)
CMA	-	0.258	0.603*
		(1.27)	(1.70)
Factors in q-4			
I/A	0.415**	-	0.860**
	(2.08)		(2.52)
ROE	3.040***	-	1.884***
	(7.63)		(4.62)
Factors in M-3			
UMO	1.523***	1.045***	-
	(6.21)	(2.92)	

Panel B: GRS F-statistic (p-value)			
HML, RMW, CMA	-	5.204 (0.002)	8.453 (2.78E-05)
I/A, ROE	37.050 (3.53E-14)	-	14.506 (1.44E-06)
UMO	35.645 (1.24E-08)	11.917 (6.93E-04)	-

국문 초록

한국 주식시장에서 가격설정오류 요인의 역할

서울대학교 대학원

경영학과 재무금융전공

이 용 우

본 연구는 Yuan and Stambaugh (2017)에서 제시된 가격설정오류 요인과 시장 요인을 결합한 3 요인 모형이 코스피 시장에서는 다른 4 요인 혹은 5 요인 모형보다 아노말리를 설명하는 데 있어서 우월한 성과를 보이지만 전체 주식시장과 코스닥 시장에서는 그러지 못한 것을 확인했다. 가격설정오류 요인은 아노말리들의 랭킹을 평균함으로써 전체 시장과 코스피 시장에서는 3 개의 주요 아노말리, 코스닥 시장에서는 6 개의 아노말리가 가진 정보를 포함하고 있다. 또한, 한국 주식 시장이 미국 시장보다 높은 공매도 위험과 규제를 가지고 있음에도, 한국 주식시장에서는 투자자 심리가 아노말리에 영향이 없는 것으로 나타났다.

주요어: 아노말리, 투자자 심리, 가격설정오류 요인

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