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M.S. THESIS

Capturing the Level, Slope and Curve Factor of Stock Returns in Korea

한국 주식시장에서의 수준, 기울기, 곡률 요인 모형에 대한 연구

BY

Tae Uk Seo

AUGUST 2016

DEPARTMENT OF BUSINESS ADMINISTRATION
THE GRADUATE SCHOOL
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지도교수 채 준

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서 태 욱

서 태 욱의 경영학석사 학위논문을 인준함

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Abstract

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Using Clarke (2016)'s procedure, I construct and test a Level, Slope, and Curve (LSC) Factor Model of stock returns in Korea. Built using a nearly identical specification to the US version, the model reflects characteristics of the cross section of expected returns in Korean stocks, by the means of reversed pattern in the curve factor. It is also robust to a number of time series and cross-sectional sensitivity checks. Moreover, a set of asset pricing tests run on 80 test asset portfolios suggests that the model prices the cross-section of expected returns to a considerable degree, and performs better than other such well known models as the CAPM, Liquidity Factor Model, and the Conditional CAPM. While the model does not yet dominate the more popular Fama and French (1993) and Carhart (1997)'s momentum factor models under its original form, it also leaves room for future progress since the model can be readily expanded to accommodate new anomalies.

Keywords: Factor Models; Level, Slope and Curve; Anomalies
Student Number: 2014-20465

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1 Introduction

The number of potential asset pricing factors is exploding in the United States, and those of the international markets closely follow suit. Harvey et al. (2016) find more than 300 factors that explain the cross-section of expected returns in the United States alone. However, due to institutional and macroeconomic differences, a direct imposition of these models to an international setting remains a difficult task. Many of the asset pricing anomalies documented in the US markets do not universally hold. Therefore, researchers in international asset pricing face a twin problem of (1) identifying the systematic risks that matter the most from the "factor zoo" (Cochrane (2011)), and (2) adjusting their estimation methods to meet the institutional differences.

Motivated by Ross (1976)'s Arbitrage Pricing Theory, Clarke (2016) takes a novel approach to construct a linear factor model of asset returns that can circumvent this issue. He constructs a level, slope, and curve model of stock returns (hereafter also referred to as "LSC") by first regressing the one-period-ahead stock returns on anomaly variables, and then extracting the first three principal components from the portfolios created by sorting the stocks by their predicted returns.

Clarke's method wields three advantages over existing beta pricing models. First, the regressions are strictly firm-specific in that all explanatory variables are individual-level. Therefore, the systematic factors are determined by principal components analysis without any assumptions introduced by a proxy for the market portfolio or other macroeconomic state variables. Second, the method by itself is relatively robust to assumptions of the researcher as no arbitrary

breakpoints are applied, and as new anomaly variables can simply be added if found. Third, a pricing framework that is consistent with that of fixed income (Litterman and Scheinkman (1988)) and foreign exchange (Lustig et al. (2011)) markets is formulated since the level, slope and curve approaches are often taken in these markets as well.

Indeed, empirical analyses suggest that the proposed model holds potential to explain the cross section of expected returns in Korea. Reflecting the unique characteristics of the Korean stock market, a LSC model constructed using Korean data exhibits a pattern similar to that of the US analog, except with a reversed pattern in the curve factor. The factors constructed using financial and accounting data since 1987 gives a sufficiently stable structure, and qualifies through a round of robustness tests in Clarke (2016). The three-factor model performs better than some other proposed asset pricing models tested in Kim et al. (2012), including the CAPM, Liquidity Factor Model, and the Conditional CAPM. However, because the Fama and French (1993) three-factor model and Carhart (1997) yet hold stronger explanatory powers, the specifications need to be better tailored to suit the anomalies in the Korean stock market.

This paper proceeds as follows. Chapter 2 describes the steps used to construct the level, slope, and curve factors of stock returns with Korean market data in detail. Chapter 3 describes the sources and key characteristics of the data used in the empirical analyses. Chapter 4 describes the key characteristics of the factors/ principal components formed using the process explained in Chapter 2. Chapter 5 conducts a preliminary in-sample time series asset pricing tests with the portfolios used to generate the factors. Chapter 6 runs cross-sectional and time series asset pricing tests using a wider class of test assets and compare the LSC model's performance with those of existing models. Chapter 7 concludes.

2 Methodology

To tailor Clarke's methodology for an international setting where accounting standards are different and where the sample size is relatively smaller, I make several adjustments to increase the explanatory power of the forecasting regression whilst maintaining much of its original specification.

The anomaly variables - except momentum, which is defined monthly - are measured each March instead of each June as in the original paper. This change is to reflect the practice that more than 80% of firms in Korea make their earnings announcements for the previous fiscal year - which ends on December - on March. However, changes across measurement months from March to June did not cause any qualitative change in the results of the subsequent analyses.

2.1 Step 1: Predictive Cross-sectional Regression

For each stock i in month t, I run the following predictive regression, identical to the original model by Clarke (2016):

$$\begin{aligned} XRet_{i,t+1} = \beta_0 &+ \beta_1 \log Size_{i,t} + \beta_2 \log {}^{B}/_{M}{}_{i,t} + \beta_3 Mom_{i,t} + \beta_4 zeroNS_{i,t} \\ &+ \beta_5 NS_{i,t} + \beta_6 NegACC_{i,t} + \beta_7 posACC_{i,t} + \beta_8 {}^{dA}/_{A}{}_{it} \\ &+ \beta_9 posOP_{i,t} + \beta_{10} negOP_{i,t} + \varepsilon_{i,t+1}. \end{aligned}$$

$Size$ stands for the market capitalization of the firm at month t, ${}^{B}/_{M}$ for book-to-market ratio, Mom for Momentum and ${}^{dA}/_{A}$ for asset growth rates. Accruals (ACC) and Operating Profit (OP) are split depending on whether they are positive or negative, and Net Issue (NS) is also decomposed into zero and

nonzero issue fiscal years. The precise definitions of the anomaly variables are available at the appendix.

Contrary to the original paper, I conduct a fully pooled regression in lieu of separate ones for micro, small, and large stocks - 20, 50 and 80th respectively - on the basis of market capitalization. This adjustment is to accommodate the smaller sample size in the Korean equity market data.

2.2 Step 2: Monthly Portfolio Sorts

Next, 15 value-weighted portfolios are formed by sorting the stock returns by the *expected* returns from the above regression each month. Again, I use 15 instead of 25 portfolios as in the original paper to accommodate the difference in the number of assets per period. However, as to be discussed further in the subsequent section, the principal components are fairly robust to the number of portfolios employed.

2.3 Step 3: Principal Components Analysis

Finally, principal component analysis is used on the estimated covariance matrix of the 15 value-weighted portfolio returns to extract the level, slope and curve factors. The principal components are formed by a linear combination of the portfolio returns using the extracted factor loadings as weights. Following Campbell et al. (1997), the loadings are re-scaled so that they sum to one in order to yield an intuitive portfolio interpretation.

3 Data

I obtain the daily and monthly price and return data for all non-financial, common stocks listed on the Korean Stock Exchange from FnGuide from January 1986 to March 2016. The accounting figures for the corresponding firms are also downloaded from the annual report panel compiled by the same vendor. The bond yields and consumption growth rates used for the risk-free rate and definition of other factors used in the horse race are from the Bank of Korea's Economic Statistics Database (BOK ECOS) and the National Statistics Portal (KOSIS).

As momentum factors require 12-months of leading raw returns for their identification and as series of the risk-free rate proxy - the 364-day monetary stabilization bond - returns are available only since January 1987, our effective factor panel begins on April 1987 and ends in December 2015.

The competing models to be explained in Section 6 are constructed for the same horizon except for cases where observations are inevitably consumed during factor identification, or where additional data is not available. For example, the Consumption CAPM model requires that the researcher run an explanatory regression of individual excess stock returns on seasonally adjusted consumption growth rates based on 36 months' data, and thus the dataset is begins from April 1990. Moreover, the monthly wage growth rates for Conditional CAPM are only available starting January 1993, and requires the same estimation procedure; therefore the factor data begins from April 1996 in this case.

4 The Factors in Detail

4.1 Characteristics across Expected Return Portfolios

Table 4.1 and Figure 4.1 show the results of the initial cross-sectional Fama-Macbeth regressions with each firms' excess return to the risk-free rate on other firm-level characteristics. The realized returns of all the 15 portfolios are monotonically increasing in line with the predicted returns. However, unlike the US version, there is also a considerable room for improvement as the variances of the predicted and realized values are vastly different.

In spite of this shortcoming, the sorted portfolios provide a simultaneous snapshot of several well-known asset anomalies previously documented in the United States and Korea. Consistent with existing literature as in Kim et al. (2012), the portfolio returns are almost strictly increasing in book-to-market ratios (B/M) and decreasing in market capitalization (Size) measured at the end of March of each calendar year. A negative momentum effect (Mom) is observed across the predicted return portfolios and the realized portfolio returns are decreasing in net share issues (NS) as well.

On the other hand, some anomaly variables do not produce such a clear-cut picture. No asset growth puzzle is documented in Korean data as the asset growth rate(dA/A) is increasing in expected returns, and accruals and operating profits follow a curve-shaped pattern.

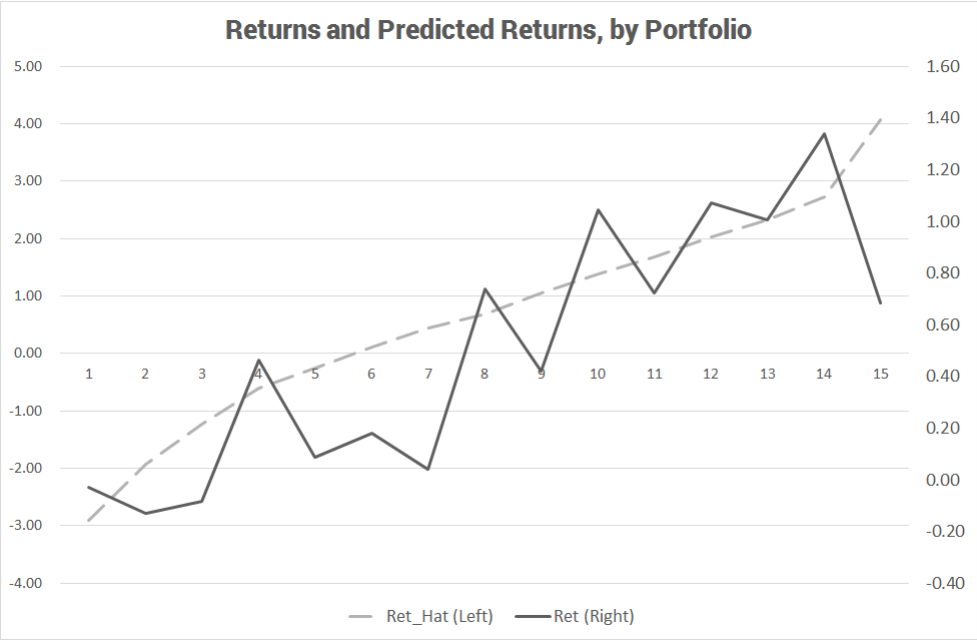

Figure 4.1 Returns and Predicted Returns, by Portfolio

The figure shows the loadings of the first three principal components of 15 anomaly portfolios, sorted by their expected returns.

4.2 Properties of Factor Loadings

The results of the subsequent principal components analysis are shown on Table 4.2 and Figure 4.2. Figure 4.2 plots the weightings of the level, slope, and curve portfolios across the expected return brackets. Overall, the first three components explain 87% of all the variances in the portfolio returns.

The first component resembles a market portfolio with approximately equal weights across assets - hence the name level factor - and explains about 78% of the total variance in 15 portfolio returns. The magnitude is consistent with Clarke (2016)'s observation that the first component explains more than 74% of variation in monthly US stock returns.

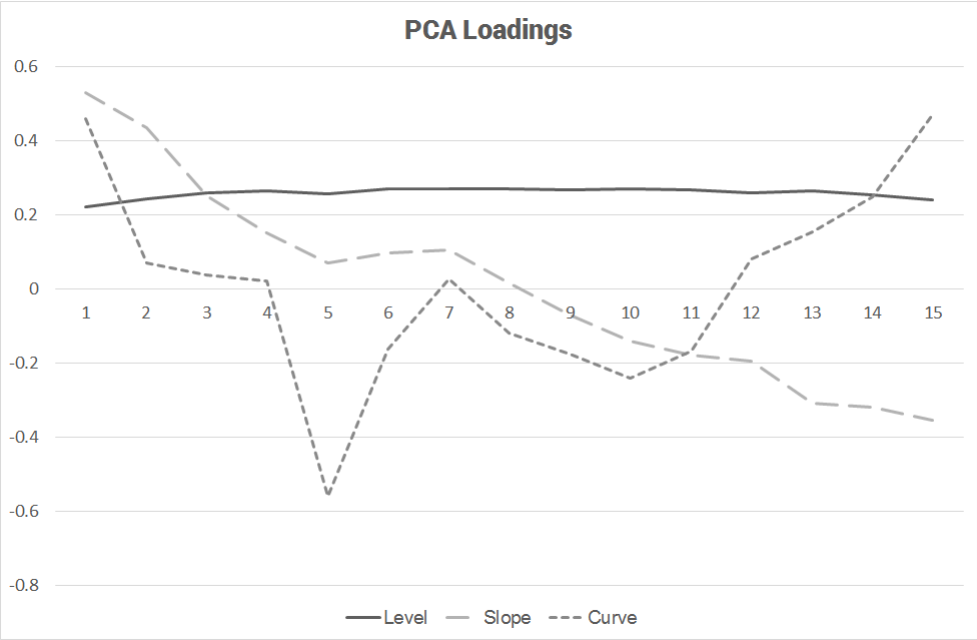

Figure 4.2 PCA Loadings

The figure shows the loadings of the first three principal components of 15 anomaly portfolios, sorted by their expected returns.

The second component, "slope", assumes a long position in the low return portfolio and a short position in the high return portfolio. Most asset pricing factors, such as the *SMB*, *HML* and *MOM*, are slope factors in that they assume monotonically varying weights across assets.

Finally the third factor assumes a long position on the extreme ends of the portfolios and goes short on the middle predicted return portfolios. The parabolic shape of the factor loadings gives the third component the name "curve" factor. A major difference with US curve factor exists, in that the signs of the factor loadings are reversed to a U-shape. While Clarke does not provide a definitive explanation for the reversed parabolic loadings, this may

be due to the differences in the magnitude and direction of the higher moments such as skewness and kurtosis of returns. Harvey et al. (2010) show that it is important to incorporate higher moments in portfolio selection under a Bayesian framework, and that considerable heterogeneity in higher moments are present across international markets. Since Korean market are known to feature lower levels of skewness and kurtosis relative to the US, the lower presence of tail risk may induce a greater long position of the tail portfolios and a short position in the middle portfolios.

On Table 4.3, I provide a correlation table of the first 5 components with other factors to confirm the above remarks. The first component indeed exhibits a 93.6% correlation with the market portfolio. While the second "slope " component is distinct, it is moderately correlated with all other asset pricing factors. In particular, the second component shows a -52.7% correlation with SMB and -49.2% with HML. The other three principal components are almost uncorrelated with the existing factors.

4.3 Robustness of Factor Loadings

Given the forecasting return regression model, the principal components obtained are robust at the cross-section and across time series.

Cross-sectionally, the properties of the first three components are stable regardless the number of portfolios used. In Table 4.4, I present the cross-correlation table of the first five components using different number of portfolios, at 5, 15, and 50. The benchmark 15-portfolios first component is 99.8% correlated with that formed using 5 portfolios, and 99.5% with one formed using 50 portfolios. Similarly the baseline second component shows a 97.4% pairwise correlation with the 5 portfolios version and 87.3% with the 50 portfolios ver-

sion.

The robustness of the third component is little lower with 57.2% for the 15-50 pair, and even more so with fourth and fifth components. However, the robustness of the first three components are exhibited to considerable degrees overall.

To test the time series stability of factor loadings, I divide the sample data into halves and perform out-of-sample analysis. Each period spans for 172 months: one from April 1987 to August 2001 and another from September 2001 to December 2012. I use only one half to estimate the factor loadings, and then apply the estimated factor loadings to the other half to generate out-of-sample principal components. If the factor structures are stable, then (1) the out of sample off-diagonal elements should be close to orthogonal as in the in-sample components, and (2) the out of sample correlation coefficients should be similar regardless of they were formed using the first or second half sample.

Table 4.5 displays the results. The last three rows and columns of the first panel show that the correlation structure of the principal components are retained in the second half of the sample even if the loadings were formed in with the first-half sample only. The off-diagonal elements are not considerably deviant from zero at $0.31, 0.20, 0.06$ for the pairs $(2,1), (3,1)$ and $(3,2)$. Similarly, the off-diagonal first-half correlation coefficients formed with second-half sample in the second panel are $-0.03, -0.10, 0.13$ for pairs $(2,1), (3,1), (3,2)$. Moreover, the correlations between the beginning and end samples are similar regardless of the portfolio formation period. The correlation matrices between the beginning and end components are -0.24, 0.06, -0.32 for the first panel, and -0.38, 0.06, -0.32 for the second panel.

Table 4.1 15 Portfolios, Sorted by Their Expected Returns ($\widehat{XRet}$)

The table shows the result of the initial cross-sectional Fama-Macbeth Regressions with each firms return on size, book-to-market, momentum, net stock issues (and a dummy for 0), accruals split into positive and negative, asset growth, and operating profit. The regression is run on every March of the year from 1987 to 2015. The firms are sorted into 15 value-weighted portfolios each month on the basis of the out-of-sample forecasting regressions. The table shows value-weighted excess returns, predicted returns and characteristics. All characteristics are in rates or ratios except Size, in billions of Korean won.

Rank	XRet	$\widehat{\text{XRet}}$	Size	B/M	Mom	dA/A	NS	Acc	OP
1	0.39	-2.33	55,577	0.60	0.19	0.11	0.04	-0.19	0.21
2	0.15	-1.20	17,120	0.81	0.14	0.11	0.02	-0.10	0.18
3	0.65	-0.47	8,738	1.11	0.10	0.11	0.02	-0.12	0.17
4	0.32	-0.02	6,115	1.26	0.09	0.11	0.02	-0.12	0.15
5	0.46	0.36	4,477	1.36	0.10	0.11	0.03	-0.13	0.15
6	0.61	0.66	5,776	1.51	0.08	0.16	0.02	-0.08	0.14
7	0.78	1.05	1,634	1.53	0.10	0.16	0.02	-0.08	0.15
8	1.04	1.35	914	1.67	0.08	0.15	0.03	-0.09	0.14
9	1.07	1.63	528	1.81	0.09	0.14	0.01	-0.07	0.14
10	0.93	1.89	349	1.95	0.08	0.14	0.00	-0.05	0.14
11	1.35	2.17	310	2.25	0.12	0.14	0.00	-0.06	0.14
12	1.67	2.46	181	2.47	0.09	0.15	0.01	-0.07	0.13
13	1.72	2.77	161	2.78	0.07	0.20	0.03	-0.06	0.13
14	1.83	3.13	111	3.19	0.06	0.19	0.02	-0.03	0.12
15	0.89	4.19	1,513	5.27	0.09	0.88	-0.07	-0.11	0.17

Table 4.2 Principal Components Analysis on 15 Anomaly-sorted Portfolios

The table shows principal components analysis on the returns of the 15 anomaly portfolios. I form anomaly portfolios using Fama-Macbeth regression on seven anomaly variables, differentiated on their signs.

Component	Eigenvalue	Difference Explained	Cumulative
1	11.908	79.39%	79.39%
2	0.865	5.77%	85.15%
3	0.330	2.20%	87.35%
4	0.274	1.83%	89.18%
5	0.224	1.49%	90.67%
6	0.213	1.42%	92.09%
7	0.180	1.20%	93.30%
8	0.170	1.13%	94.43%
9	0.155	1.03%	95.46%
10	0.145	0.97%	96.43%

Table 4.3 Cross-Correlation Table of the First Five Components

The table shows cross-correlation of the Level, Slope and Curve factor to the market factor, SMB, HML, Momentum, Profitability, Liquidity as well as Consumption-CAPM and Conditional CAPM factors.

Variable	Prin1 (Level)	Prin2 (Slope)	Prin3 (Curve)	Prin4	Prin5
$r_m - r_f$	0.936	0.275	0.128	-0.030	-0.012
SMB	-0.059	-0.527	-0.100	-0.190	0.124
HML	0.238	-0.492	-0.080	0.034	-0.113
MOM	-0.145	0.226	-0.227	-0.027	0.152
PROF	-0.117	0.241	-0.128	-0.171	0.119
INV	-0.227	-0.330	-0.021	0.239	-0.061
CONSU	-0.008	-0.114	-0.058	0.103	0.049
LABOR	0.178	0.166	0.130	0.060	0.034
DEF	0.059	0.271	0.090	-0.046	0.148

Table 4.4 Cross-Correlation Table of the First Five Components

In each panel, the table shows the correlation of each of the first five principal components with the matching component formed using a different number of portfolios.

First Component			
	5 Portfolios	15 Portfolios	50 Portfolios
5 Portfolios	1.000		
15 Portfolios	0.998	1.000	
50 Portfolios	0.990	0.995	1.000
Second Component			
	5 Portfolios	15 Portfolios	50 Portfolios
5 Portfolios	1.000		
15 Portfolios	0.974	1.000	
50 Portfolios	0.797	0.873	1.000
Third Component			
	5 Portfolios	15 Portfolios	50 Portfolios
5 Portfolios	1.000		
15 Portfolios	0.794	1.000	
50 Portfolios	0.435	0.572	1.000
Fourth Component			
	5 Portfolios	15 Portfolios	50 Portfolios
5 Portfolios	1.000		
15 Portfolios	0.098	1.000	
50 Portfolios	-0.098	-0.291	1.000
Fifth Component			
	5 Portfolios	15 Portfolios	50 Portfolios
5 Portfolios	1.000		
15 Portfolios	-0.156	1.000	
50 Portfolios	-0.013	-0.097	1.000

Table 4.5 Cross-Correlation Table Separating Beginning and End of Sample

In each panel, the table shows the correlation of each of the first three principal components from the beginning of the sample, thus the beginning sample principle components are formed in sample and compared with the out of sample principal components formed using principal components on the second half of the sample. The second panel shows the correlations of components in the latter half of sample. The End components are in sample and compared with the out of sample Beg components that were formed using only data from the first half of the sample.

Beginning of Sample						
	Beg 1	Beg 2	Beg 3	End 1	End 2	End 3
Beg 1	1.00					
Beg 2	0.00	1.00				
Beg 3	0.00	0.00	1.00			
End 1	-0.24	0.27	-0.16	1.00		
End 2	0.15	0.06	0.17	0.31	1.00	
End 3	0.41	0.07	-0.32	0.20	0.06	1.00
End of Sample						
	Beg 1	Beg 2	Beg 3	End 1	End 2	End 3
Beg 1	1.00					
Beg 2	-0.03	1.00				
Beg 3	-0.10	0.13	1.00			
End 1	-0.38	0.28	-0.18	1.00		
End 2	0.23	0.06	0.19	0.00	1.00	
End 3	0.55	0.07	-0.32	0.00	0.00	1.00

5 In-Sample Time-Series Asset Pricing Tests

Before comparing the performance of the LSC model with that of other models, I take a closer look at how LSC model fares with each of the 15 test portfolios used to construct the model.

Table 5.1 displays the results of the time series regression of the expected return sorted portfolios on the extracted principal components. The columns the realized excess returns of the portfolios, the intercepts and their corresponding t-statistics, and the adjusted R-squareds from the regression on the first, two, three and four principal components.

Evidently, the adjusted R-squareds are monotonically increasing as more components are added. While more than half of the total variation in returns is explained by the first principal component (level) for all 15 portfolios, there also exists considerable difference in the explanatory powers. The R-squared of the regression for the first component is largest at the middle portfolios - with the 8th portfolio reaching 0.869 - whereas those of the extreme portfolios are substantially lower at 0.585 for portfolio 1 and 0.684 for portfolio 15. Note that this difference is not due to heterogeneity in number of assets that constitute each portfolio - which may be the case when the portfolios are generated through multiple independent sorts - since I only sort the portfolios by their expected returns.

This is where the addition of additional components play a role despite their relatively smaller incremental contribution to the R-squareds. The variance in

Table 5.1 Time Series Regressions of 15 Expected Return Sorted Portfolios on the Extracted Principal Components

The table shows regression results of the 15 portfolios formed using the anomaly regressions on the extracted principal components. Each portfolio is regressed on the first one, two, three and four principal components. The alpha and its t-statistics plus the adjusted R-squareds from each regression are displayed.

Portfolio	Ret	α	t	R_1^2	R_2^2	R_3^2	R_4^2
1	-0.03%	-0.280%	-2.600	0.585	0.828	0.897	0.950
2	-0.13%	-0.140%	-0.835	0.697	0.861	0.862	0.896
3	-0.08%	0.078%	0.395	0.795	0.848	0.848	0.848
4	0.46%	0.191%	1.015	0.824	0.843	0.843	0.856
5	0.09%	0.128%	0.828	0.786	0.790	0.893	0.894
6	0.18%	0.290%	1.781	0.862	0.869	0.877	0.877
7	0.04%	0.425%	2.348	0.864	0.873	0.873	0.877
8	0.74%	0.652%	3.654	0.869	0.869	0.873	0.874
9	0.42%	0.773%	4.268	0.847	0.851	0.861	0.861
10	1.04%	0.919%	6.184	0.865	0.882	0.901	0.911
11	0.72%	0.852%	4.848	0.844	0.871	0.881	0.880
12	1.07%	0.983%	4.710	0.792	0.825	0.827	0.849
13	1.01%	1.221%	8.080	0.824	0.906	0.914	0.915
14	1.34%	1.612%	9.878	0.763	0.852	0.872	0.910
15	0.68%	1.244%	10.906	0.684	0.792	0.865	0.960

R-squareds between portfolios are substantially reduced as each component is added as regressors. The standard deviation in adjusted R-squareds decreases from 7.9% to 3.1% and then to 2.2% as first one, two, and three components are included. On average, the adjusted R-squared from the first three components amount to 87.2%.

Meanwhile, we also find considerable heterogeneity in the magnitude and significance of alphas from the regressions. The alphas and their t-statistics are in an increasing trend in absolute terms in the order of portfolio returns. The

largest alpha coefficient is for the portfolio number 14, with 1.614% and the most significant one is for the portfolio 15, with a t-statistic of 10.91. While a number of drivers may be cited for this discrepancy, it possibly owes to the negative weights employed by the slope factor at the higher predicted portfolios as exhibited by Figure 2. The strong short sale restrictions posed in the Korean market over the sample period may imply that excess returns are observed in portfolios where negative loadings are employed.

6 Comparative Asset Pricing Tests and Horse Races with Existing Models

In this section, I conduct a comparative asset pricing test of the Level, Slope and Curve factor of stock returns in both cross-sectional and time series perspectives. I also run a horse race of alternative factors against the model to determine if the model sufficiently explains variations in other factors.

6.1 Test Assets

For the asset pricing tests and horse races, I use the following 80 test assets.

- 25 portfolios formed on size and book-to-market.
- 10 portfolios sorted by momentum.
- 10 portfolios formed on operating profit.
- 10 portfolios formed on investment.
- 10 FnGuide industry portfolios[1].
- 15 predicted return portfolios from Section 3.

I employ a relatively large size of test assets - compared to the typical $25 = 5 \times 5$ Size and Book-to-Market independent sort portfolio is often used in Korea - in order to provide a level playing field for all 8 cross-sectional asset pricing

[1] The definitions are available at the appendix.

models. While Clarke (2016) uses an even larger group that consists of 119 test assets, the difference arises from the number of industry portfolios, since Clarke uses 49 instead of 10 industry portfolios based on Fama and French's industry definitions.

6.2 Competing Model Specifications

Using the aforementioned 80 test assets, the level, slope, and curve factor model is gauged against 7 other asset pricing models. I compare the LSC model with Sharpe (1964) and Lintner (1965)'s Capital Asset Pricing Model, the Fama and French (1993) 3-factor model, the Carhart (1997) momentum factor model, the CNZ (Chen, Novy-Marx, and Zhang (2011)) profitability and investment model, an APT-motivated liquidity factor model à la Kim, Kim and Shin (2012), linearized consumption CAPM model, and a Conditional CAPM model by Jagannathan and Wang (1996).

6.2.1 The Capital Asset Pricing Model

I employ the conventional Capital Asset Pricing Model:

$$R_{i,t} - R_{f,t} = \beta_{i,m}(R_{m,t} - R_{f,t}) + \epsilon_{i,t}.$$

The Risk-free Rate Proxy

Following Kim et al. (2012) as well as Kho and Kim (2007), I choose the 364-day monetary stabilization fund returns to proxy for the risk-free rate ($R_{f,t}$). The returns are calculated from the yield data available at the Bank of Korea Economic Statistics System (BOK ECOS) by the following formula:

$$R_{f,t} = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{\left[1/(1+y_{t-1})^{11/12}\right] - \left[1/1+y_{t-1}\right]}{1/1+y_{t-1}}.$$

The Market Risk Premium

The market risk premium ($R_{m,t} - R_{f,t}$) is the value-weighted return with dividends of all stocks listed on the Korea Exchange (KRX) in excess of the risk-free return.

6.2.2 The Fama and French 3-Factor Model

$$R_{i,t} - R_{f,t} = \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \epsilon_{i,t}.$$

Following Kho and Kim (2007), the Size (*SMB*) and Book-to-Market (*HML*) are constructed from an independent two-by-three sort on size and book-to-market as in Fama and French (1993). At the end March of each year, all stocks are ranked on market capitalization and book-to-market ratios. *SMB* is the return of a zero-cost, equally weighted portfolio that goes long on the bottom 50% size and short on the top 50% size. *HML* is the return of a zero-cost equal-weighted portfolio that assumes a long position on the top 30% book-to-market ("value") stocks and a short position on the bottom 30% book-to-market ratio ("growth") stocks.

6.2.3 The Carhart 4-Factor Model

$$R_{i,t} - R_{f,t} = \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \epsilon_{i,t}.$$

Following Carhart (1997), I first sort the stocks into deciles by momentum, or the cumulative continuously compounded 11 months' stock return from month $t-2$ to $t-1$. A momentum factor (*MOM*) is constructed by taking a long position on the top decile and a low position on the bottom decile portfolio. The equally-weighted portfolios are rebalanced every month.

6.2.4 The CNZ Profitability and Investment Model

$$R_{i,t} - R_{f,t} = \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,PROF}PROF_t + \beta_{i,INV}INV_t + \epsilon_{i,t}.$$

As in Lee and Ohk (2015), Profitability (*PROF*) is generated as a function of return on equity, defined as the proportion of net income as of March in the current year to book equity in the previous year. The stock returns are sorted by ROE every March and *PROF* is defined as the difference in the equally weighted returns between the top 30% and bottom 30% portfolios.

Investment (*INV*) factors are defined in the same fashion. Investment is measured by the investment to asset ratio (I/A), defined as the annual change in gross, property, ploant and equipment plus the annual change in inventories divided by the lagged book value of assets. I sort the stock returns by I/A every March and INV_t portfolio is defined as the difference in the equally weighted returns between the bottom 30% I/A and top 30% I/A stock portfolios.

6.2.5 The Liquidity-based APT Model

$$R_{i,t} - R_{f,t} = \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,LIQ}LIQ_t + \epsilon_{i,t}$$

Following Kim et al. (2012), I sort each stock by Amihud (2002)'s liquidity measure obtained using the daily returns and volumes in the past 12 months:

$$Amihud_{i,t} = -\frac{1}{N_{it}}\sum_{k=1}^{N_{it}}\frac{|R_k|}{VOL_k}.$$

The liquidity factor (*LIQ*) is constructed as a portfolio that goes long on the top 20% most illiquid stocks and short on 20% most liquid stocks.

6.2.6 The Consumption CAPM Model

$$R_{i,t} - R_{f,t} = \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,CONSU}CONSU_t + \epsilon_{i,t}.$$

At the end of March each year y, I estimate the following OLS equation using past 36 months' data available up to December of year $y-1$:

$$R_{i,t} - R_{f,t} = \gamma_{0,it} + \gamma_{1,it}\dot{c}_t + \varepsilon_{i,t}$$

where $R_{it} - R_{ft}$ is the monthly stock return in excess of the risk-free rate, and $\dot{c}_t$ is the real, seasonally adjusted consumption growth rate transformed to monthly level. The quarterly consumption growth rate - obtained from the Bank of Korea ECOS item 'Composition of final consumption expenditure of households by type, real sa' (Korean: 가계의 형태별 최종소득지출, 계절조정 실질, 분기) - is converted to monthly frequency using cubic spline interpolation. I leave a term of 3 months from December of year $y-1$ to allow time for the information release.

Next, using the estimated stock return sensitivities to consumption $\hat{\gamma}_{it}$ a Consumption factor "*CONSU*" is created by going long the 20% of high-$\hat{\gamma}$ firms and going short the 20% of low-$\hat{\gamma}$ firms.

6.2.7 The Jagannathan and Wang Model

$$R_{i,t} - R_{f,t} = \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,LABOR}LABOR_t + \beta_{i,DEF}DEF_t + \epsilon_{i,t}.$$

The Jagannathan and Wang (1996) version of conditional CAPM includes a market risk premium component, a labor factor to accommodate non-traded component of human capital, and a default premium to reflect default risk and business cycle conditions.

For the labor factor, I obtain the nominal monthly average wage data for businesses with 10+ employees from Korea Statistics Portal under the section MOEL Labor Force Survey at Establishments (Korean: 고용노동부 사업체노동력조사, 全산업 全규모 10인이상 사업체 1인당 월간 임금총액) and apply the following three steps to convert it to real, seasonally adjusted wage growth rate.

Step 1: the data is converted to real terms by dividing it by the Bank of Korea GDP deflator.

Step 2: X-12 ARIMA is applied to seasonally adjust the series.

Step 3: The data is log-differenced.

As with the consumption factor, at the end of March of each year y, I estimate the OLS equation using past 36 months' data available up to December of year $y-1$:

$$R_{i,t} - R_{f,t} = \lambda_{0,it} + \lambda_{1,it}\dot{w}_t + \varepsilon_{i,t}$$

where $\dot{w}_t$ is the real, seasonally adjusted wage growth rate that proxies for the labor income in Jagannathan and Wang (1996).

A long-short portrfolio ($LABOR$) is finally formed by going long the 20% of high-$\hat{\lambda}$ firms and short the 20% low-$\hat{\lambda}$ firms' stocks.

On the other hand, the default spread (DEF) is the difference between the 3-year AA-rated corporate bond yield and the 3-year Treasury bond yield. The 3-year financial debentures yield issued by the Korean Development Bank is used prior to the introduction of the treasury bond on May 1995.

6.3 Asset Pricing Tests

I run both time series and cross-sectional tests to gauge the LSC model in reference to the aforementioned counterparts.

For each test asset and model pair, the time series tests simply run the regression

$$R_{i,t} - R_{f,t} = \alpha_i + f_{1t}\beta_{i1} + \cdots + f_{nt}\beta_{in} + \varepsilon_{i,t} \qquad \forall t = 1, 2 \ldots T,$$

where $R_{it} - R_{ft}$ is the excess return of the test asset, f_{nt} are returns of factor mimicking portfolios in an asset pricing model, and n is the number of factors in the model. A well-specified asset pricing model should find high R-squareds and low significance and magnitudes of intercepts ("alphas").

For the cross-sectional tests, I adapt the Jensen et al. (1972)'s approach of first estimating the full-sample betas of each test asset on the level, slope,

and curve factors using time series regressions, and then regressing the average returns on the estimated betas.

$$\bar{R}_i - \bar{R}_f = \gamma_0 + \hat{\beta}_{i1}\gamma_1 + \cdots + \hat{\beta}_{in}\gamma_n + \eta_i.$$

The cross-sectional tests provide three testable implications to measure the explanatory power of the asset pricing model. The R-squared of the cross-sectional regression should be close to 1 as the assets should be priced by the systematic factors. The constant term should be close to zero and near the risk-free rate. Finally, the coefficients of the cross-sectional regressions - $\hat{\gamma}$s - should be close to the average return on the factor mimicking portfolios.

Table 6.1 presents the results of the asset pricing tests at time series and cross-sectional levels. The average of adjusted R-squareds for the level, slope and curve factor model well exceeds those of other renowned asset pricing models, including the Novy-Marx profitability and investment model, liquidity based APT, the consumption and conditional CAPMs. Furthermore, the mean absolute pricing errors (MAPE, $|\alpha|$) of the LSC model is lower than the aforementioned models as well. However, the model underperforms the Fama-French 3 factor model and Carhart's 4-factor model in terms of adjusted R-squareds and MAPE.

Similar results are reported in the cross-sectional tests on Panel B, however with greater reservations. The LSC model exhibits higher R-squareds than the plain vanilla CAPM, liquidity factor model, and conditional CAPM. Furthermore, the constant term is closest to zero with the exception of the Carhart model and is also insignificant unlike the CAPM, Novy-Marx, CCAPM and Conditional CAPM estimation results.

Yet, while the slope and curve factors are significantly priced in terms of t-statistics, I cannot reject the null that the level factor is a systematic risk

factor as is the case for Fama-French and Carhart models. Therefore the model is not free from the so-called Fama and French critique that the "(market) beta is dead". Moreover, the dominance of R-squareds by the two models suggests that a more refined specification of the anomalies regression will be necessary to raise the explanatory power of the LSC models.

6.4 Horse Races and Limitations

Finally, a horse race is run to determine what factors are important in explaining the cross-section of returns in terms of their marginal explanatory powers. As in Clarke (2016), I follow Cochrane (2005)'s procedure to conduct factor horse races. First, OLS regressions are run with returns on each individual aset pricing factor. When the estimated coefficient is added to a cross-sectional asset pricing test with other factors, the resulting coefficient estimate yields the marginal significance of the factor. If a factor is insignificant, it adds little explanatory power to the model.

Table 8 displays the results of the horse race, with each factor added to the LSC model. One finds that the factors previously considered important in the Korean data such as the SMB and Investment lose their significance when they are run against the LSC model. However, the LSC model cannot dominate other factors such as the market risk premium, momentum, profitability and consumption. Therefore, while the LSC model does hold several useful promises, it by alone cannot serve as a representative asset pricing model that best reflects the cross-section of equity returns in the Korean market at this stage.

Table 6.1 Comparing Level, Slope and Curve to Leading Factor Models with 80 Test Portfolios

Panel A: Time Series Test Results								
Factor	LSC	CAPM	FF3	CAR	CNZ	LIQ	CCAPM	JW
Avg $\|\alpha\|$	0.65	0.6766	0.5343	0.5079	0.6739	0.6862	0.7289	1.0361
$\|t\| > 1.96$ of 80	40	40	31	30	33	40	38	28
Avg R^2	0.7143	0.623	0.7368	0.7494	0.6364	0.6876	0.6201	0.6423
Panel B: Cross-Sectional Test Results								
Factor	LSC	CAPM	FF3	CAR	CNZ	LIQ	CCAPM	JW
β Level	-0.162							
	(-0.42)							
β Slope	-0.154***							
	(-3.70)							
β Curve	0.113*							
	(2.00)							
β Market		-2.086**	-1.543	-0.734	-2.306**	-1.502	-1.235	-1.610*
		(-2.65)	(-1.59)	(-0.78)	(-3.21)	(-1.44)	(-1.92)	(-2.16)
β SMB			0.449*	0.362				
			(2.22)	(1.89)				
β HML			0.999***	1.174***				
			(3.64)	(4.48)				
β MOM				1.417**				
				(3.33)				
β PROF					1.724***			
					(4.51)			
β INV					0.00199			
					(0.01)			
β LIQ						0.976**		
						(2.77)		
β CONSU							-3.959***	
							(-4.86)	
β LABOR								-0.549
								(-0.80)
β DEF								0.0651
								(0.55)
Constant	0.738	2.240**	1.525	0.720	2.551***	1.627	1.505*	1.867*
	(0.83)	(3.06)	(1.60)	(0.78)	(3.81)	(1.58)	(2.49)	(2.56)
adj. R^2	0.129	0.071	0.199	0.299	0.232	0.068	0.261	0.023

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.2 "Horse Race" Regressions of the Level, Slope and Curve Model with Alternative Factors

	(1) LSC	(2) +MKT	(3) +SMB	(4) +HML	(5) +MOM	(6) +PROF	(7) +INV	(8) +LIQ	(9) +CONSU	(10) +LABOR	(11) +DEF
β LEVEL	-0.162	3.394*	-0.296	-0.684	0.177	0.0268	-0.174	-0.251	0.397	0.140	0.0424
	(-0.42)	(2.46)	(-0.72)	(-1.68)	(0.49)	(0.08)	(-0.45)	(-0.61)	(1.19)	(0.35)	(0.11)
β SLOPE	-0.154***	0.195	-0.225**	-0.0914*	-0.171***	-0.221***	-0.151***	-0.200*	-0.190***	-0.112*	-0.280**
	(-3.70)	(1.43)	(-2.65)	(-2.04)	(-4.54)	(-6.22)	(-3.55)	(-2.43)	(-5.05)	(-2.14)	(-3.38)
β CURVE	0.113*	0.183**	0.105	0.106	0.183***	0.117*	0.114*	0.110	0.0216	0.0387	0.0210
	(2.00)	(3.04)	(1.85)	(1.97)	(3.43)	(2.56)	(2.01)	(1.93)	(0.41)	(0.55)	(0.32)
β MKT		-9.160**									
		(-2.68)									
β SMB			-0.431								
			(-0.95)								
β HML				1.049**							
				(3.02)							
β MOM					1.951***						
					(4.33)						
β PROF						2.059***					
						(6.33)					
β INV							0.177				
							(0.46)				
β LIQ								-0.371			
								(-0.64)			
β CONSU									-5.735***		
									(-6.46)		
β LABOR										0.123	
										(0.14)	
β DEF											0.573*
											(2.55)
Constant	0.738	0.843	1.217	1.716	-0.0715	0.495	0.763	1.056	-0.271	0.387	0.930
	(0.83)	(0.98)	(1.19)	(1.89)	(-0.09)	(0.68)	(0.85)	(1.03)	(-0.36)	(0.42)	(1.03)
adj. R^2	0.129	0.195	0.128	0.213	0.294	0.425	0.120	0.122	0.421	0.010	0.089

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Summary and Discussion

To conclude, the paper explores whether the Level, Slope and Curve Factor model proposed by Clarke (2016) has the potential to serve as an asset pricing model that best reflects the cross-section of expected returns in the Korean stock market. The model contains three factors that hold distinct loadings across baseline portfolios, with level factor behaving closely with a market portfolio, a slope factor representing a long-short strategy and a curve factor assuming a U-shaped "barbell" position. The factors are robust to cross-sectional and time series variations, and are not subject to assumptions by the researcher except the forecasting regression.

Even with a baseline model specified in an almost identical fashion to US analog and not tailored to the Korean market, the asset pricing tests show that the LSC model performs better than several incumbents including the CAPM, Liquidity APT and the conditional CAPM. However, it still lags behind the more generally models such as the Fama-French and Carhart models.

Hence, the LSC model is clearly far from an exact identification in the Korean market. However, its strength as a model that holds both the flexibility of the regression equation and the robustness from cross-sectional and time series deviations suggest that the model holds useful promises for further research.

8 Appendix

The List of Variable Definitions Used for Anomalies Regression

I download the Accounting and Equity Market data from the DataGuide Pro database provided by FnGuide (`http://www.dataguide.co.kr/`). The monthly 364-day Monetary Stabilization Bond (MSB) return is obtained from the Bank of Korea Economic Statistics System (`http://ecos.bok.or.kr`). The forecasting (anomaly) variables are:

Size: Market cap, the natural log of price times shares outstanding at the end of March of year t.

$^{B}/_{M}$ Book-to-market equity, the natural log of the ratio of the book value of equity to the market value of equity. Following Kho and Kim (고봉찬, 김진우 2008), the book value of equity is calculated as the sum of contributed capital to common shares, additional paid-in capital, retained earnings, deferred tax liabilities less treasury stocks for year $t-1$. Market value of equity is price times shares outstanding at the end of December $t-1$.

NS Net stock issues, the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year end in $t-1$ divided by the split-adjusted shares outstanding at the fiscal year in $t-2$. The split-adjusted shares outstanding is shares outstanding divided by cumulative adjustment factor from FnGuide.

Acc	Accruals, the cash flows from operating activities less earnings in $t-1$, divided by book equity in $t-1$.
Mom	Momentum, the cumulative continuously compounded stock return from March of $t-1$ to end of January (two months prior to measurement).
${}^{dA}/_{A}$	Growth in assets, the natural log of the ratio of assets at the fiscal year $t-1$ divided by assets at fiscal year $t-2$.
OP	Profitability, operating income divided by book equity in year $t-1$.

Industry Classification Codes

To classify the stocks into Industry-based portfolios, I use the FnGuide Industry Classification Standard (FICS). The use of FICS in lieu of the Industry codes from KRX is intended to address concerns that the KRX codes do not fully take into account of within-industry connections as they are product-based.

Code	Classification	Median No. of Firms	Sample Begins
FICS.10	Energy	17	1981:01
FICS.15	Materials/ Chemicals	190	1981:01
FICS.20	Industrials	198	1981:01
FICS.25	Consumer Goods (High-beta, durables)	198	1981:01
FICS.30	Consumer Goods (Low-beta, food products)	73	1981:01
FICS.35	Medical/Pharmaceuticals	51	1981:01
FICS.40	Financials	76	1981:01
FICS.45	Technology	105	1981:01
FICS.50	Communications	7	1989:12
FICS.55	Utilities	9	1981:01

초록

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본 논문은 Clarke (2016)의 방법론을 이용하여 한국 주식시장에서의 수준, 기울기 및 곡률 (LSC) 요인모형을 제시하고 검증한다. 미국 시장에서와 거의 동일한 방식으로 구축된 동 모형은 곡률요인의 가중치 차이 등을 통해 한국 시장의 특수성을 반영하는 한편, 시계열과 횡단면 차원에서 강건성을 나타낸다. 아울러 80개 검증대상자산(Test assets)을 대상으로 실시된 실증분석 결과는 LSC 요인모형이 CAPM, 유동성 요인모형 및 조건부 CAPM 등 기존 모형보다 높은 설명력을 지니는 등 기대수익률의 변동을 상당 부분 설명함을 시사한다. 다만 현재의 기초 모형설정 하에서는 Fama and French (1993)의 3요인 모형 및 Carhart (1997)의 모멘텀 모형 등 보다 자주 활용되는 모형보다는 설명력이 부족한 것으로 나타나 본 방법론의 유연성을 토대로 이상현상(Anomalies)을 더욱 반영하여 모형의 적합도를 개선할 필요가 있음을 지적한다.

주요어: 요인모형, 주식의 수준 · 곡률 · 기울기 모형; 이상수익률현상
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