

# The Effect of Credit Risk on Stock Returns\*

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## Abstract

This paper investigates the effect of credit risk on the return of stocks. We construct the systematic factor in relation to credit risk using the credit spreads of individual firms constructed using the Merton (1974, Journal of Finance) model. This enables us to include firms without credit spreads or ratings information in our analysis so that we are free of the sample selection bias. The credit factor captures a systematic risk in the Korean stock market, which the standard Fama-French three factors (market, size and value) and the momentum factor cannot fully explain.

*Keywords:* Equity Return; Credit Risk; Implied Credit Spread; Credit Factor; Fama-French Factors

## 1. Introduction

A stock price is traditionally considered to be the present value of future dividend payments. When a firm defaults, no more dividends are paid to equityholders and the stock price drops to almost zero. This leads us to interpret equity as a debt with the last seniority that pays dividend as coupon. From this, we can infer that equities are subject to credit risk as corporate debts are.

Previous empirical works on equity multi-factor models such as Fama and French (1993) and Chen, Roll and Ross (1986) use aggregate corporate bond spread indices, which are grouped by credit ratings (AAA and BAA ratings for example), for capturing factors related to credit risk. This approach can induce a sample selection bias because not every firm issues bonds. Also, credit ratings often fail to provide a firm's credit status in a timely manner.

We take a different approach to look at credit risk at the level of the individual firm. Instead of using the aggregate indices, we focus on individual credit spreads implied from the equity market using the structural credit risk model by Merton (1974). One can use the credit spread that can be obtained from corporate bonds or credit default swaps price data. However, it requires a well-developed credit market where credit instruments are liquidly traded, which is not the case for most countries. Also, the market credit spread can be influenced by liquidity that is not uniform across firms. For example, in the credit default swaps market, the names listed in CDS indices (CDX or iTraxx) are more liquidly traded than others. So even when the market spread is available, it is still desirable to use model-implied credit spreads.

The purpose of this paper is to investigate the effect of credit risk on stock returns, especially in the Korean stock market. If we suppose a common risk source for credit risk, we can expect that firms with higher credit risk are more exposed to this systematic risk related to credit risk. Using the implied credit spread as a firm characteristic that represents credit risk, we construct a credit risk factor following Fama and French (1993). More specifically, we define the credit factor as the return difference between the portfolios of

stocks with high and low implied credit spreads. Then we examine whether this factor is fully explained by the well-known factors such as the Fama-French three factors (market, size and value factors) and the momentum factor by Jegadeesh and Titman (1993). The result shows that the credit factor generates statistically significant alpha when it is regressed on those four factors. This implies that it captures a systematic risk that the standard Fama-French three factors and the momentum factor cannot explain.

Similar to ours, Vassalou and Xing (2004) use the implied default probability based on the same Merton model. The main difference from ours lies on the probability space where the credit risk measure is defined. Our credit spread is measured under the risk-neutral probability whereas Vassalou and Xing (2004) estimate the default probability under the real-world probability. This requires them to estimate the drift term of the asset return process, i.e. the expected asset return, which is subjective in nature. They use the average of the past asset returns as its estimate. This can be logically flawed if we notice that the whole purpose of the factor model is to explain the expected equity return, which can be closely related to the expected asset return.

The rest of the paper is organized as follows. In Section 2, we introduce a pricing formula for stocks that considers credit risk. Section 3 explains how we can measure the credit risk at an individual firm level applying the Merton (1974) model. Section 4 presents an empirical analysis on the Korean stock market after we construct a credit risk factor. Section 5 concludes this paper.

## 2. Credit Risk in Stock Price

This section introduces the stock price formulation in Jarrow (2001) to show how the credit risk of a firm can affect its stock price. For simplicity, we do not consider a possible bubble component in stock prices here. The market is assumed to be frictionless and free of arbitrage opportunities.

Let us consider a firm issuing equity that pays regular dividends  $D_t$  at time  $t = 1, 2, \dots, T_L$ . The firm has a liquidating dividend  $L(T_L)$  at time  $T_L$  and let  $\bar{S}(t)$  be the time

$t$  present value of this dividend unless there is no default before time  $t$ . The regular dividend payments are also conditional upon no default prior to the payment date and they are assumed to be deterministic. We can flexibly set  $T_L$  so that this assumption holds in reality. For many firms, it is fair to set  $T_L$  be equal to one year.

If we interpret equity as a debt with the last seniority, we can think of a zero-coupon bond of equity ( $e$ ) seniority and let  $v(t, j; e)$  represent its value at time  $t$  where  $j$  is the maturity time. A debt's seniority is characterized by its recovery rate at default. We can expect positive recovery rates even for equities if the possibility of revival after default is considered. However, for simplicity, we assume that the recovery rate for equity is zero.

Let  $\tau$  be a random variable that represents the default time, and consider a stochastic process  $N(t) = 1_{\{\tau \leq t\}}$  which indicates whether default happens before time  $t$ . Assume this process has an intensity  $\lambda(t)$ , called default intensity. The probability that the firm defaults over the time interval  $[t, t + \Delta]$  can be approximated by  $\lambda(t)\Delta$  for small  $\Delta$ . So the intensity  $\lambda(t)$  can be interpreted as the instantaneous default probability.

The value of the equity at time  $t$  is then given by

$$S(t) = \bar{S}(t) + \sum_{j \geq t}^{T_L} D_j v(t, j; e)$$

conditional upon no default prior to time  $t$ . Under the reduced-form credit risk modeling framework, it can be shown that

$$\bar{S}(t) = E_t^Q \left[ L(T_L) e^{-\int_t^{T_L} r(u) + \lambda(u) du} \right] \text{ and}$$

$$v(t, j; e) = E_t^Q \left[ e^{-\int_t^j r(u) + \lambda(u) du} \right]$$

where  $r(t)$  is the risk-free spot interest rate and  $E_t^Q(\bullet)$  is the conditional expectation under the risk-neutral measure  $Q$ . The existence of the risk-neutral measure is from the no arbitrage assumption. Intuitively, the discount rate for the defaultable discount factor  $v(t, j; e)$  is adjusted by the instantaneous default probability  $\lambda(t)$ . The reduced-form model has been developed by Jarrow and Turnbull (1992, 1995), Lando (1998) and Duffie and

Singleton (1999) among many others.

From the above formulation, it is clear that stock price changes as the firm's credit risk, represented by the default intensity  $\lambda$ , fluctuates. Previous studies on credit spreads such as Duffee (1998) and Elton et al. (2001) indicate that the credit risk is subject to systematic risk sources such as Government bond yields or aggregate corporate bond spread indices. Higher credit risk means the stock price is more exposed to these systematic risk sources. We do not intend to verify what fundamental variables are affecting a firm's credit risk and hence its stock price. Instead we would like to assume a common risk source for the credit risk and to see whether this risk is rewarded by the market.

### 3. Measuring Credit Risk

If credit markets are well developed and credit products such as corporate bonds or credit default swaps are liquidly traded, we can measure individual firm's credit risk directly from the prices observed in the market. However, corporate bonds are usually illiquid and credit default swaps are not available for majority of the companies in the world. Hence we apply the Merton (1974)'s structural model of credit risk to measure the credit risk at an individual firm level. The reduced-form approach introduced in the previous section is not so much useful when credit instruments are not available or liquidly traded in the market.

Merton (1974)'s model is based on the Black-Scholes-Merton model. Let  $A_t$  be a firm's asset value at time  $t$ . We assume that it is financed by equity ( $E$ ) and zero-coupon bond with face value  $D_T$  maturing at  $T$ . The firm defaults when its total asset value at maturity  $A_T$  is less than its liability  $D_T$ . Suppose the asset value follows a Geometric Brownian motion:

$$\frac{dA_t}{A_t} = \mu_A dt + \sigma_A dW_t, \quad (1)$$

where  $\mu_A$  is a drift parameter,  $\sigma_A$  is the annualized asset volatility, and  $W_t$  is a Brownian

motion. It should be noted that a firm's asset value and its volatility are not observable. Since the equity has the limited liability, the value of equity at time  $T$  can be written as

$$E_T = \max\{A_T - D_T, 0\} \quad (2)$$

So the equity is interpreted as a call option on the asset value with the exercise price equal to the face value of the firm's debt maturing at time  $T$ . From Black and Scholes (1973) and Merton (1973), the solution of the current value of equity is

$$E_0 = A_0 N(d_1) - D_T e^{-rT} N(d_2) \quad (3)$$

where

$$d_1 = \frac{\ln(A_0 e^{rT} / D_T) + \frac{1}{2} \sigma_A^2 T}{\sigma_A \sqrt{T}} \quad \text{and} \quad d_2 = d_1 - \sigma_A \sqrt{T}. \quad \text{Here } N(\bullet) \text{ is the cumulative standard}$$

normal distribution function, and  $r$  is the risk-free interest rate. Since  $E_t$  is a function of  $A_t$ , it follows from the Itô formula that

$$dE_t = \left( \frac{\partial E_t}{\partial t} + \frac{\partial E_t}{\partial A_t} A_t \mu_A + \frac{1}{2} \frac{\partial^2 E_t}{\partial A_t^2} \right) dt + \frac{\partial E_t}{\partial A_t} A_t \sigma_A dW_t. \quad (4)$$

Let us further assume that the value of the equity also follows a Geometric Brownian motion:

$$\frac{dE_t}{E_t} = \mu_E dt + \sigma_E dW_t, \quad (5)$$

where  $\sigma_E$  is the equity volatility. Matching the volatility terms the above two equations (4) and (5) gives us

$$\sigma_E = \frac{\partial E_t}{\partial A_t} \frac{A_t}{E_t} \sigma_A. \quad (6)$$

Since the hedge ratio is  $\frac{\partial E_t}{\partial A_t} = N(d_1)$ , we have

$$\sigma_E = N(d_1) \frac{A_0}{E_0} \sigma_A. \quad (7)$$

Hence we can obtain the current asset value  $A_0$  and the asset volatility  $\sigma_A$  from observable variables  $E_0$ ,  $\sigma_E$ ,  $D_T$  and  $T$  by solving equations (3) and (7) simultaneously.

The current value of debt is  $D_0 = D_T e^{-(r+s)T} = A_0 - E_0$ , where  $s$  is the credit spread.

Therefore, the implied credit spread is given by

$$s = \frac{1}{T} \ln \left( \frac{D_T}{A_0 - E_0} \right) - r, \quad (8)$$

which is denoted by SPREAD in this paper. Since SPREAD is ultimately a function of observable variables such as stock price, equity volatility and risk-free interest rate, we can compute firm-specific SPREAD.

From Lando (1998) and Duffie and Singleton (1999), the credit spread can be approximately decomposed by the default intensity  $\lambda$  and the recovery rate  $\delta$ . That is

$$s = \lambda(1 - \delta),$$

when the intensity and the recovery rate are constant. As the recovery rate information is not available, we take SPREAD as the measure of the credit risk at an individual firm level. Previous empirical works show that recovery rate is higher for firms with lower default probability, see Altman, Resti, and Sironi (2004) for a review. Thus, firms with higher default intensity have higher credit spread (SPREAD). For constructing the credit factor, we only need the order of the amount of credit risk of firms in our universe. Therefore, the lack of recovery rate information would not affect the result of this paper.

## 4. Empirical Analysis

### 4.1. Data

We test our model with the historical constituents of the Korea Composite Stock Price Index (KOSPI). Our data period is from 1995 to June 2007, spanning both the Asian Financial Crisis and recent boom in stock market. Thus, we can investigate how SPREAD is correlated with those events. We download the data from WORLDSCOPE, FactSet and Bloomberg.

The market value of equities of a firm is defined as the current price of stock times the



number of common shares outstanding. The values are retrieved via FactSet which aggregates various databases in order to minimize missing values. The face value of debt is defined as the total book value of liabilities of the firm. The time horizon we consider is one year. Since the value of liabilities change quarterly, the one third of liabilities data that we use are in fact recorded two months ago, one-month ago and this month respectively.

The equity volatility is defined as the sample standard deviation of the total returns for previous 250 days. We use FactSet price database to obtain the daily total return series of all stocks. As an approximation, the asset volatility is assumed to be the same as the equity volatility. Then we obtain the current asset value by solving the equation (3). It can also be obtained from the equation (7). The results are close to each other confirming the validity of our approximation.

#### **4.2. Constructing Credit Risk Factor**

We construct portfolios based on the implied credit spread (SPREAD) 20% quintiles and examine the cumulative excess return of the portfolios over the KOSPI200 as a benchmark. Using KOSPI or sample average as a benchmark gives nearly the same result. The universe is all the stocks that have ever been listed on KOSPI in order to eliminate survivorship bias. We assume monthly rebalancing with a one-month portfolio formation period. Thus, we use information at  $t - 1$  in order to construct a portfolio at  $t$  and observe returns at  $t + 1$ . So the expected return is approximated using next one-month return.

Figure 1 shows how SPREAD can explain cross-sectional differences between next one-month stock returns. We can see that the stock with a higher SPREAD exhibits a higher expected return in most of the period, which is in line with our intuition.

Another interesting pattern is the relationship between SPREAD and the Asian Financial Crisis. The Asian Financial Crisis spanned from early 1997 to 1999, when Korean government declared the end of the crisis. The graph shows that firms with low credit risk outperformed those of high credit risk during that period. Over the course of the financial crisis, a large number of corporations went bankrupt. The reverse pattern is possibly due to

the flight-to-quality within the stock market.

[Figure 1]

To see the SPREAD pattern more clearly, we define the credit factor as the difference between portfolio returns at the top and bottom of the SPREAD. More specifically, the credit factor is the excess return of a portfolio with long high credit spread stocks and short low credit spread stocks. The risk that affects the performance of the portfolio is solely from the credit spread information. Since the second quintile of SPREAD shows a more stable pattern, we define two credit factors (CREDIT FACTORs) for robustness of our analysis.

- CREDIT FACTOR: Return difference between portfolios formed with stocks in the top 20% and the bottom 20% of the SPREAD;
- CREDIT FACTOR 2: The difference between the top 20% - 40% and the bottom 20% of the SPREAD.

Figure 2 shows the CREDIT FACTOR cumulative excess return. It suggests that the premium on CREDIT FACTOR is positive on average. It also shows a noticeable pattern of sudden drops and surges during the Asian Financial Crisis.

[Figure 2]

#### **4.3. Implied Credit Spread and the Macro Events in Korea**

We further investigate the relationships among the business cycle, stock returns and the implied credit spread. Figure 3 presents the interconnections. The bar graph denotes equally weighted implied credit spread (bps), and the dotted line is the cumulative stock returns (%) of KOSPI200.

[Figure 3]

As clearly illustrated in the figure, the average SPREAD is related to business cycles and the stock market. More specifically, the three important economic events in Korea after the late 1990s – the Asian Financial Crisis, Dot-com Burst and Credit-Card Crisis<sup>1</sup> – are in line with the three hikes in the average SPREAD.

Figure 4 illustrates the distribution of implied credit spread as of May 2007.

[Figure 4]

#### **4.4. Relationship with Other Factors and Pricing**

Here we investigate how the two CREDIT FACTORS are related with other risk factors. We perform a typical alpha-test whether the CREDIT FACTORS show significant alphas even after controlling for various risks. We regress CREDIT FACTOR and CREDIT FACTOR 2 on the three and the four factor models, respectively. Thus, we have four results. The three factor model is based on the three Fama-French factors: market, size and value factors. The four factor model has a momentum factor in addition to the three Fama-French factors. The momentum phenomenon is well explored in Jegadeesh and Titman (1993) and Chan, Jegadeesh and Lakonishok (1996). The detailed construction and the dynamics of the four factors in Korean stock market are shown in the Appendix.

Tables 1 through 4 present the results showing a presence of significant positive premiums. The positive premium is often called as alpha. In an efficient market, a positive premium should not exist unless we take risk. This means that our SPREAD captures either

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<sup>1</sup> “Credit card use expanded by a factor of eleven between 1998 and 2002, preceding the development of adequate expertise in the credit card companies and in the supervisory authorities. The rise in the delinquency ratio from 5 to 14 per cent and in the amount of rescheduled loans from 7 to 29 per cent of total credits led to serious liquidity and capital problems in this sector. In response, the government has encouraged related companies to roll over the debt of the credit card companies, although such a strategy tends to weaken market discipline. The authorities co-ordinated a rescue of the largest credit card company, fearing that its collapse could lead to a systemic crisis” (OECD, 2004).

the risks that standard risk models cannot fully explain or statistical arbitrage opportunities if we drop the assumption of the market efficiency.

[Table 1]

[Table 2]

[Table 3]

[Table 4]

#### **4.5. Risk Source Analysis**

Chan, Karceski and Lakonishok (1998) propose an approach to identify the factors inducing variation in stock returns. Instead of investigating expected returns, they examine the volatility of factors one-by-one in univariate manners. Since the factors are constructed from the returns of large portfolios with zero investment strategies, it is reasonable to assume that idiosyncratic risks are diversified away. So the standard deviation of a factor represents the amount of exposure to systematic risk sources that generate market comovement. Table 5 illustrates the results.

[Table 5]

The results show that the CREDIT FACTOR can explain market comovement better than the market, value and momentum factors and that it is as good as the size factor at explaining market comovement. Thus we can conclude that the CREDIT FACTOR is an important source of risk.

In addition, notice that the size and the value factors are positively correlated with the credit risk factor, 0.8358 with the size factor and 0.7455 with the value factor. Often, the Fama-French three factor model is criticized by its lack of economic intuition for selecting the factors. The high correlation with the credit risk factor implies that the Fama-French factors (size and value) can be partially explained by credit risk.

## 5. Conclusion

In this paper, we consider a credit risk factor for the multi-factor equity pricing model. A firm's credit risk can be explicitly incorporated into its stock price formula through the default intensity if we consider that future dividend payments are contingent on default event. We suggest the credit spread implied by the Merton model as a firm characteristic that represents credit risk. The credit risk factor is then constructed from the factor-mimicking portfolio with long high credit spread stocks and short low credit spread stocks. The empirical test on the Korean stock market shows that the credit risk factor exhibits significantly positive premiums even after controlling the standard Fama-French three factors and the momentum factor.

## Appendix

### A. Fama-French Factors in Korea

We construct factors with all Korean stocks available in FactSet. Also, we use the top 20% and bottom 20% of stocks in terms of size, book-to-market ratio, and momentum to define the factors. We recalculate the factors every month. Thus, we select the top and bottom 20% of stocks in month  $t$  and compute factor returns over  $t$  and  $t+1$ . We use equal weights to form the portfolios.

- Market factor: We define the market factor as the excess return of the KOSPI200 over 3-month CD rates. The KOSPI200 comprises the largest stocks in the KOSPI composite index and is defined as the free-float capital-weighted average of the constituents. The 3-month CD rate is the proxy for the risk-free rate, as referenced from Bloomberg.
- Value factor: We define the value factor as the excess return of those stocks in the top 20% by book-to-market (B/P) ratio versus those in the bottom 20%.
- Size factor: We define the size factor as the excess return of those stocks in the bottom 20% by size versus those in the top 20%. The size is a sum of market values of stocks and liabilities.
- Momentum factor: We define the momentum factor as the excess return of the stocks within the top 20% in terms of momentum versus those in the bottom 20%. Momentum is defined as returns over the past six-months.

Figure 5 shows the dynamics of the four factors.

[Figure 5]

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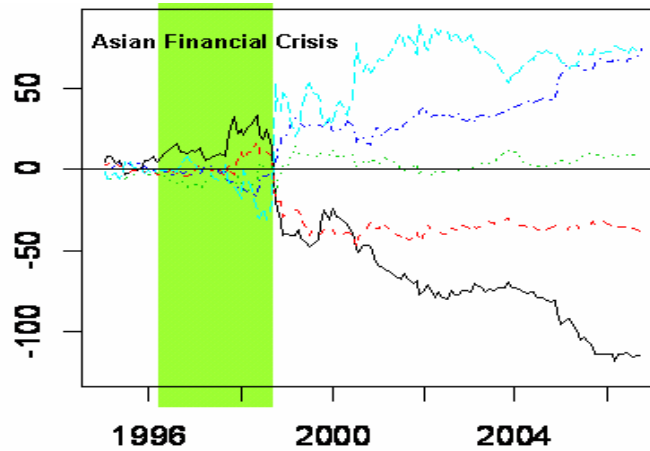
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## Figures and Tables

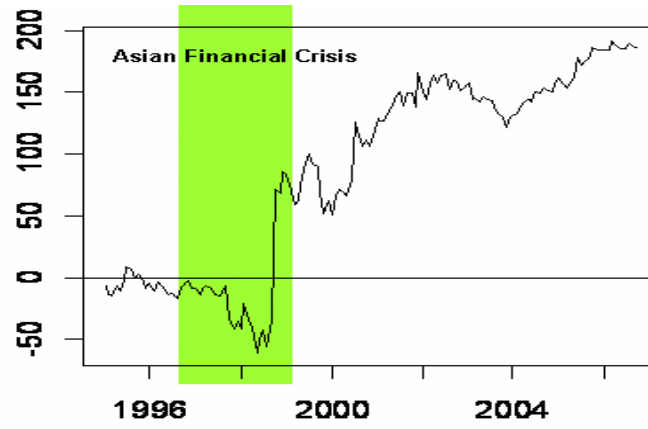
Figure 1: Portfolio Performances sorted with SPREAD



The graph specifies the cumulative excess return of portfolios over benchmark. The portfolios are constructed based on the implied credit spread (SPREAD) 20% quintiles. Benchmark is KOSPI200. Using KOSPI or sample average as benchmark gives nearly same results. The universe is all the stocks that have ever been listed on KOSPI in order to eliminate survivorship bias. By the order of the size of credit spread, the light blue, blue, green, red and black lines are the cumulative returns of the portfolios from the largest implied credits spread to smallest. We assume monthly rebalancing with a one-month portfolio formation period. Thus, we use information at  $t-1$  in order to construct a portfolio at  $t$  and observe returns at  $t+1$ . The Asian Financial Crisis spanned from early 1997 to 1999, when Korean government declared the end of the crisis. Highlights are added in order to distinguish the totally different dynamics during the Financial Crisis relative other time periods.

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Figure 2: CREDIT FACTOR Dynamics (cumulative)

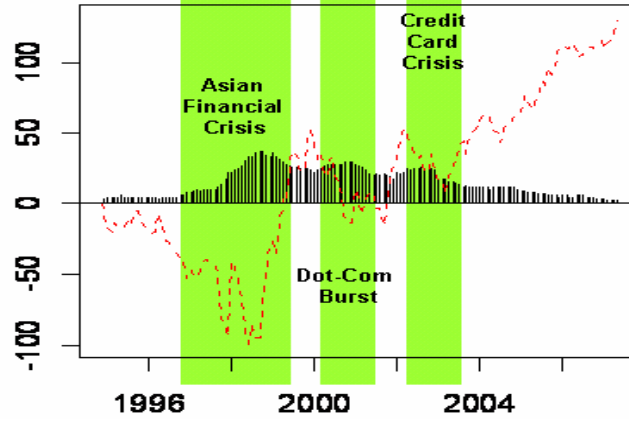


The graph specifies the CREDIT FACTOR cumulative return, defined with the differences in returns between portfolios formed with the largest and the lowest implied credit spread. The portfolios are constructed based on the implied credit spread 20% quintiles. The Asian Financial Crisis spans from early 1997 to 1999, when the Korean government declared the end of the crisis. Highlights are added in order to emphasize the totally different dynamics around the financial crisis relative other time periods.

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Figure 3: Average Implied Credit Spread and Cumulative KOSPI200 Returns

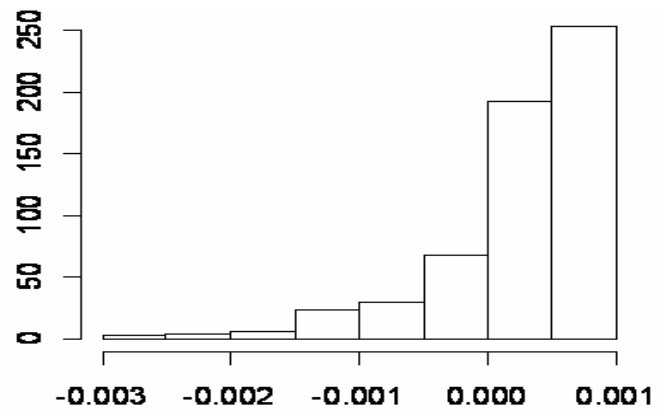


The bar graph denotes equally weighted implied credit spreads (bps). The dotted line is the cumulative stock returns (%) of KOSPI200. Shaded area stresses the period of the Asian Financial Crisis (1997-1999), Dot-com Bust (2002) and the Credit Card Bubble & Crisis (2002-2003).

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Figure 4: Distribution of the Logarithm of SPREAD as of May 2007



Histogram of  $\log(\text{SPREAD})$

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Table 1: Alpha Test (CREDIT FACTOR against Fama-French Three factor)

Residuals:

Min	1Q	Median	3Q	Max
-23.782	-3.508	-0.552	4.587	16.848

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	1.36331	0.52776	2.583	0.0108	*
marketf	-0.02429	0.05121	-0.474	0.6361	
sizef	0.59261	0.05122	11.571	< 2e-16	***
valuef	0.47319	0.07510	6.301	3.34e-09	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.115 on 145 degrees of freedom

Multiple R-Squared: 0.7691, Adjusted R-squared: 0.7643

F-statistic: 161 on 3 and 145 DF, p-value: < 2.2e-16

We use the top 20% and bottom 20% of stocks in terms SPREAD. We recalculate the factors every month. Thus, we select the top and bottom 20% stocks in month t and compute factor returns over t and t+1. The table shows the results of a regressing credit spread factor on the three factors under consideration.

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Table 2: Alpha Test (CREDIT FACTOR against Fama-French Three factor + Momentum)

Residuals:

Min	1Q	Median	3Q	Max
-19.2411	-2.8624	-0.1678	3.7122	14.4750

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	1.22548	0.49371	2.482	0.0142	*
marketf	-0.03571	0.04789	-0.746	0.4571	
sizef	0.53198	0.04952	10.742	< 2e-16	***
valuef	0.34512	0.07520	4.589	9.59e-06	***
momentumf	-0.27442	0.05815	-4.719	5.56e-06	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.711 on 144 degrees of freedom

Multiple R-Squared: 0.8, Adjusted R-squared: 0.7945

F-statistic: 144 on 4 and 144 DF, p-value: < 2.2e-16

We use the top 20% and bottom 20% of stocks in terms of SPREAD. We recalculate the factors every month. Thus, we select the top and bottom 20% stocks in month t and compute factor returns over t and t+1. The table shows the results of a regressing credit spread factor on the four factors under consideration.

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Table 3: Alpha Test (CREDIT FACTOR 2 against Fama-French Three factor)

Residuals:

Min	1Q	Median	3Q	Max
-28.0372	-3.1455	0.1522	3.4618	17.5055

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	1.51260	0.54707	2.765	0.006435	**
marketf	-0.01033	0.05309	-0.195	0.845991	
sizef	0.61559	0.05309	11.595	< 2e-16	***
valuef	0.30755	0.07785	3.951	0.000121	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.339 on 145 degrees of freedom

Multiple R-Squared: 0.7198, Adjusted R-squared: 0.714

F-statistic: 124.2 on 3 and 145 DF, p-value: < 2.2e-16

We use the top 20% - 40% and bottom 20% of stocks in terms of SPREAD. We recalculate the factors every month. Thus, we select the top and bottom 20% stocks at month t and compute factor returns over t and t+1. The table shows the results of a regressing credit spread factor on the three factors under consideration.

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Table 4: Alpha Test (CREDIT FACTOR 2 against Fama-French Three factor + Momentum)

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Residuals:
      Min       1Q   Median       3Q      Max
-27.95614  -2.81961  -0.05596   3.08063  19.28644

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.39921    0.52622   2.659 0.008726 **
marketf     -0.01973    0.05104  -0.386 0.699717
sizef        0.56571    0.05279  10.717 < 2e-16 ***
valuef       0.20218    0.08015   2.523 0.012738 *
momentumf    -0.22577    0.06198  -3.643 0.000376 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.087 on 144 degrees of freedom
Multiple R-Squared:  0.7434,    Adjusted R-squared:  0.7363
F-statistic: 104.3 on 4 and 144 DF,  p-value: < 2.2e-16

```

We use the top 20% - 40% and bottom 20% of stocks in terms of SPREAD. We recalculate the factors every month. Thus, we select top and bottom 20% stocks at month t and compute factor returns over t and t+1. The table shows the results of a regressing credit spread factor on the four factors under consideration.

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Table 5: Factor Standard Deviations and Correlations

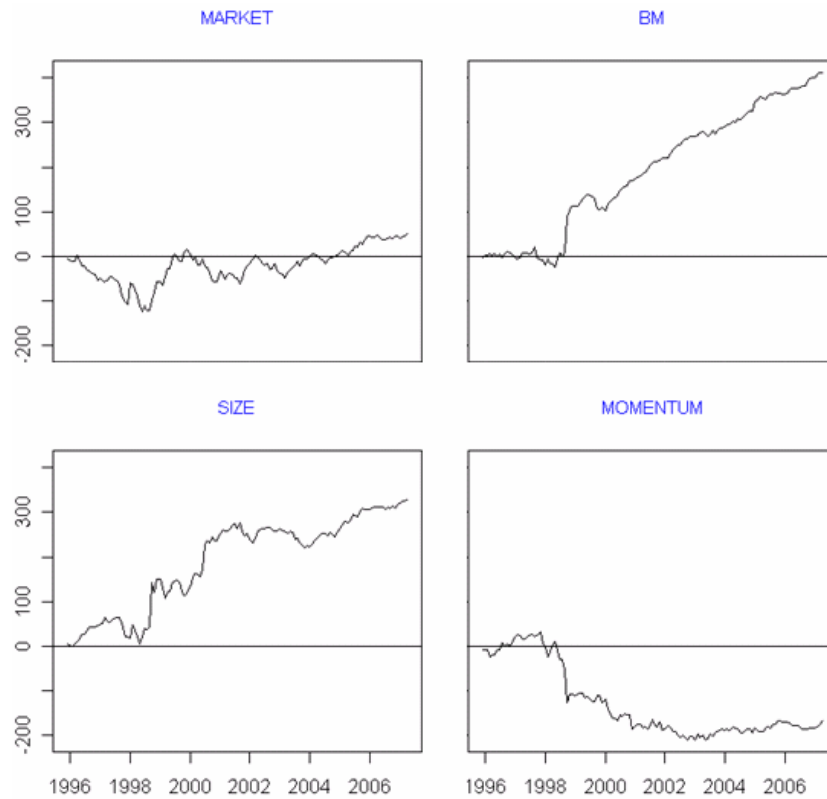
	Stdev.	creditf	marketf	sizef	valuef	momentumf
creditf	12.597400	1.0000000	-0.1990706	0.8358351	0.7455434	-0.6697456
marketf	10.242065	-0.1990706	1.0000000	-0.1371259	-0.2793189	0.1121224
sizef	12.964293	0.8358351	-0.1371259	1.0000000	0.6516467	-0.5414082
valuef	9.121138	0.7455434	-0.2793189	0.6516467	1.0000000	-0.5825926
momentumf	10.306267	-0.6697456	0.1121224	-0.5414082	-0.5825926	1.0000000

The first column in the above is standard deviations. Credit has higher monthly volatility than other usual factors. Columns 2–6 are a correlation matrix among factors.

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Figure 5: Fama-French Three Factors and Momentum Factor in Korea



We construct the factors with the stocks existing in the FactSet database. Also, we use the top 20% and bottom 20% of stocks in terms of size, book-to-market ratio and momentum to define the factors. We recalculate the factors every month. Thus, we select top and bottom 20% stocks at month  $t$  and compute factor returns over  $t$  and  $t+1$ .

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