Identifying the Statistical Factors of Credit Spread Changes on Corporate Bonds: Evidence from the US Industrial Sector[+]

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Abstract

Identifying the factors that drive credit spread changes is a challenging task for risk management. It is a major concern for most international sectors and in particular the US industrial sector. Statistical methods such as Principal Components Analysis possess considerable explanatory power but they do not admit readily of any meaningful interpretation. The aim of this paper is to interpret the statistical factors derived from Principal Components Analysis, explaining US industrial sector Credit Spread Changes from January 2001 to December 2004. This study shows that the first six factors, which explain **79.9%** of credit spread changes, can be interpreted. Specifically, the first statistical factor corresponds to the Corporate Bond Market Index. The second corresponds to the equity volatility factor. The third factor is associated with leverage ratios. The fourth factor is related to coverage ratios. The fifth corresponds conjointly to profitability and liquidity ratios. Finally, the sixth factor represents stock momentum factor. Our results confirm that monthly credit spread changes are mainly driven by equity market factors and provide evidence in favour of incorporating stock momentum factor to explain credit spread changes.

Keywords: Credit spread changes, Principal Components Analysis, Statistical factors, Equity Market Factors.

JEL Classifications: C10, G19.

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1 Introduction

Credit markets have undergone a dramatic change over the past few years. Identifying the forces that drive corporate bonds has received increasing attention in the last decade, among academics (see, for example, Duffee (1998, 1999), Duffie and Singleton (1999), Collin-Dufresne, Goldstein, and Spencer-Martin (2001), Elton, Gruber, Agrawal, and Mann (2001)), practitioners and financial regulators. This growing attention is due in large part to the size of the corporate bond markets and the proposals of the Basle Committee on Banking Supervision to reform the prudential standards of the capital required for banks' credit risks. Corporate bonds typically trade at higher yields than Treasury bonds of comparable maturities. The yield spread is partly due to the credit risk of corporate bonds, and is thus commonly referred to as "credit spread". A manager's performance of corporate bonds portfolios is largely conditioned by his aptitude to anticipate future prices, and specifically credit spread.

Despite the remarkable growth of the credit risk market, there are limited empirical studies on the behaviour of credit spread changes. This is mainly due to the limited availability of data. The most interesting empirical results on credit spread changes are those developed by Brown (2000), Collin-Dufresne, Goldstein, and Martin (2001) and Elton, Gruber, Agrawal, and Mann (2001).

Brown (2000) explores the influence of the 10-year Treasury yield, consumer confidence, the VIX index and a Treasury bond liquidity measure on credit spread changes for Salomon Brothers bond indexes. He finds that these variables account for approximately 33% of the total inertia of credit spread changes. Collin-Dufresne, Goldstein, and Martin (2001) find that a large part of the dynamics of US corporate credit spread cannot be explained by variables of structural models of corporate bond pricing such as changes in leverage, changes in the yield curve, the economic environment and volatilities. Furthermore, these authors argue that a single systematic factor explains a large proportion of residual credit spread changes. Elton, Gruber, Agrawal, and Mann (2001) study the explanatory power of compensation for expected defaults, compensation for state taxes, and compensation for systematic risk relative to government bond returns on the changes of credit spread.

The purpose of our study is to interpret the statistical factors obtained from Principal Components Analysis (PCA) which explain credit spread changes in the US industrial sector between January 2001 and December 2004. For that, we use the methodology developed in Ben Hassine and Charpin (2005) and Ben Hassine (2005), applied to the American and French equity market, respectively. It consists of projecting some portfolios onto K-factorial axes obtained from PCA. These portfolios are formed according to the methodology developed by Fama and French (1992, 1993, 1996). In this study, we form portfolios on the basis of two kinds of factors: Accounting Ratios (Coverage, Leverage, Profitability and Liquidity ratios) and Equity Market Factors (stock momentum and equity volatility).

The main findings are as follows. First, we can interpret the statistical factors derived from Principal Components Analysis with a direct approach. Second, we confirm the link between credit spread changes and equity market factors, consistent with predictions from structural models of corporate bond pricing. Lastly, our results suggest that in addition to equity market variables and accounting ratios, stock momentum factor may also help explain credit spread changes.

The remainder of this paper is organized as follows. Section 2 describes the main theoretical determinants of credit spread changes. In section 3, we present the methodology and the explanatory variables used in our empirical study. In section 4, results and interpretations are presented. Section 5 presents our conclusions.

2 The main theoretical determinants of Credit Spread Changes

Since the 1970s, there has been an enormous amount of theoretical modelling of credit spread. Two major groups of models are generally used: structural and reduced-form models. Structural models of default, built on the option pricing theory of Black and Scholes (1973), use the evolution of a firm's structural variables, such as asset and debt value, to determine the time of default. Merton's model (1974)[1], which represented the first structural credit risk model, assumes that default occurs when the firm value falls below its outstanding debt. More specifically, in Merton's model, a firm issues two types of assets: equity and a zero-coupon bond with maturity T and face value of D, which it is assumed is the only source of debt. The value of a default-risky zero-coupon bond at time T equals the difference of the value of a default-free zero-coupon bond with face value D and the value of a European put option with maturity T and strike price D on the asset value. Therefore, the value of the equity can be considered as the value of a European call option on the firm's asset value. This approach assumes that default can only happen at the maturity of the zero-coupon bond and provides a link between the credit quality of a firm and its asset value and capital structure.

In contrast to the structural models, where default occurs as soon as a firm's asset value falls below a certain threshold, the reduced-form models (also known as intensity-based models), developed by Jarrow and Turnbull (1995), Jarrow, Lando and Turnbull (1997), Duffie and Singleton (1999) and Madan and Unal (1998), assume that default happens at any time. Thus, reduced-form models specify the credit event as an unpredictable event governed by a hazard-rate process. Despite this fundamental difference, major factors such as the risk-free rate, the asset value and the asset volatility and their effect on credit spread are common to these two models.

[1] See also Longstaff and Schwartz (1995), Leland (1994), Leland and Toft (1996), Collin-Dufresne, Goldstein and Martin (2001).

In what follows, we briefly present the main theoretical determinants of credit spread changes.

1. Changes in Spot Rate. Longstaff and Schwartz (1995) argue that an increase in spot rate increases the risk-neutral drift of the firm-value process. This reduces the probability of default and in turn reduces the credit spread. This negative relation between the spot rate and credit spread changes has been also confirmed by Duffee (1998).

2. Changes in Slope of the Yield Curve. Many empirical studies[2] document that the slope of the default-free term structure, which is often measured as the spread between the long-term and the short-term rate, can explain the behaviour of credit spread changes. An increase in the slope increases the expected short-term interest rates, thereby reducing credit spread.

3. Changes in Leverage. According to the structural framework, high leverage should increase the default event and in turn increase credit spread.

4. Changes in Volatility. The contingent-claims approach assumes that firm value is driven by the firm's total volatility. This approach considers debt such as a combination of a risk-free loan and a short put option on the firm. High asset volatility increases the option value and therefore bond prices' credit spread will increase. Some authors (see, for instance, Campbell and Taksler (2003)) consider, in particular, idiosyncratic volatility.

5. Changes in Liquidity. Collin-Dufresne et al. (2001), Houweling et al. (2002) and Perraudin and Taylor (2004) argue that liquidity influences credit spread changes significantly: the lower the liquidity in corporate bond markets, the higher the credit spread. Van Landschoot (2004) proxies liquidity by the bid-ask spread: "narrowing bid-ask spread indicate greater liquidity and thus lower credit spread".

[2] See, for instance, Litterman and Scheinkman (1991) and Chen and Scott (1993).

6. Changes in Market conditions. Even with constant default probability, changes in credit spread are influenced by changes in the expected recovery rates. Since the expected recovery rate is a function of the overall business climate (Altman and Kishore (1996)), an improving economy leads to a decrease of credit spread. To proxy changes in the business climate, we can use equity market returns (Collin-Dufresne et al. (2001)).

3 Database and Methodology

3.1 Data Description

In this section, we present the source of credit spread and the description of the explanatory variables. These variables represent firm-level fundamentals which are based on issuer equity data.

1. Credit spread. The data set consists of monthly option-adjusted spread[3] (OAS) for 758 US industrial sector corporate bonds available in Merrill Lynch over the period December 2000 to December 2004. The bonds in question, whose emission amount is at least of $250[4] million, are composed of 624 investment grade bonds (AAA-BBB3) and 134 speculative grade bonds (BB1-B3) issued by 208 Tickers. The different categories of rating are provided by Merrill Lynch. The rating used in this study represents an average of Standard & Poor's (S&P) and Moody's classification. It is important to note that each bond present in our sample represents 49 consecutive[5] monthly observations of credit spread. Likewise important are the bonds whose credit spread data appears to be problematic (for example, a bond whose value of credit spread is negative) were eliminated from our final sample.

We determine monthly credit spread changes from the corresponding monthly credit spread series. For example, the monthly credit spread changes for January 2002 is measured as the difference

[3] The option-adjusted spread, stated in basis points, have the advantage of being purged of any embedded options and coupon effects. It represents a refinement over the traditional spread measure.
[4] This restriction represents the new criterion of inclusion in the Merrill Lynch index.
[5] In other words, we have excluded bonds that have gone bankrupt or that have expired (maturity date before December 31, 2004) and that issue date is after December 31, 2000.

between the credit spread on January 30, 2002 and the spread on December 31, 2001. Finally, we have 48 monthly observations from January 2001 to December 2004.

Table 1 presents some descriptive statistics of the data over the sample period. The average of credit spread changes for our entire sample is –3.89 basis points (bps), ranging between -1.33 bps and -11.15 bps, and having a standard deviation average of 37.19 bps. Focusing on this table, we remark that when the ratings tend to be worse, the changes increase. In fact, the highest-grade AAA has a credit spread standard deviation of 6.51 bps, while the lowest-grade B3 has a 483.23 bps standard deviation.

Rating categories	Number of bonds	Mean (Bps)	Std Dev. (Bps)	Min (Bps)	Max (Bps)
AAA	10	-1.90	6.51	-18.90	10.10
AA2	6	-1.33	6.64	-25.33	11.16
AA3	26	-1.39	5.06	-19.65	10.96
A1	51	-1.84	9.28	-27.62	32.43
A2	104	-2.18	7.75	-28.98	17.11
A3	70	-2.22	8.39	-24.61	24.25
BBB1	44	-3.15	7.86	-25.38	25.09
BBB2	203	-2.27	12.44	-37.02	27.79
BBB3	110	-2.89	21.43	-67.03	75.05
BB1	25	-4.12	32.35	-96.68	89.00
BB2	37	-9.07	38.64	-148.59	79.02
BB3	28	-6.66	47.44	-137.85	111.42
B1	23	-4.02	57.39	-188.34	144.26
B2	8	-4.09	160.06	-461.25	589.37
B3	13	-11.15	136.61	-293.00	483.23

Table 1: Descriptive Statistics for monthly credit spread changes in the US industrial sector

2. Corporate Bond Market Index. In this study, we use the monthly option-adjusted spreads of US Global Broad Market Industrial Index (GOBI) as a proxy of the movements in US corporate bond Market. The data set are obtained from Merrill Lynch over the period December 2000 to December 2004.

3. Equity volatility. For each corporate bond, we determine the corresponding equities' 12-month volatility at the end of each fiscal year during the period December 2000-December 2003. Equity volatility is computed as the annualized standard deviation of the natural log of the ratio of two successive prices. These series are provided directly by JCF[6].

4. Stock momentum. We define stock momentum at time t as the cumulative return over the six months ending at the beginning of the previous month. So, we compute a 6-month stock momentum at the end of each fiscal year from 2000 until 2003. The stock returns are obtained from Datastream database.

The following variables are computed on the basis of COMPUSTAT's annual industrial files of key ratios, income-statement and balance-sheet data. In first step, we calculate all the different accounting ratios at the end of each fiscal year from 1999 until 2003. Afterwards, we compute the changes[7] of these different ratios at time t (t=2000, 2001, 2002 and 2003). In fact, the majority of empirical studies on credit spread changes (for example, Collin-Dufresne, Goldstein, and Spencer-Martin (2001) and Van Landschoot (2004)), use changes in accounting ratios rather than levels.

5. Leverage ratios. We use two types of leverage measures. The first one corresponds to *Net Debt* which is defined as Long-term Debt plus Short-term Debt less Cash and Equivalents. We compute this measure at the end of each fiscal year from 1999 until 2003. Afterwards, we compute *Net Debt* changes at time t (t=2000, 2001, 2002 and 2003). The second leverage measure is calculated by dividing Net Debt by (Market Value of Equity + Net Debt). For each corporate bond, market values of firm equity are obtained from JCF.

6. Coverage ratios. We distinguish two ratios: *EBITDA/Interest Expense* and *Net Operating Cash Flow / Net Debt.* EBITDA (Earnings before Interest, Tax, Depreciation and Amortisation) is the sum of Operating

[6] The JCF (Jacques Chahine Finance) database offers financial and macroeconomic data (among others) with Microsoft Excel functionality.
[7] In our study, we consider the change of a ratio at year t as the growth rate of this ratio between the year t and the year (t-1).

Income and Depreciation and Amortisation. Interest Expense is directly obtained from the COMPUSTAT database. The ratio *EBITDA/Interest Expense* represents a measure used by firms to assess credit quality. The *Net Operating Cash Flow / Net Debt* is determined by dividing Net operating cash flow, which is directly obtained from the COMPUSTAT database, by Net Debt.

7. **Profitability ratios.** We use *Net Margin* as a profitability ratio. This concept is equals to Net Income divided by *Sales/Turnover (Net)*. This ratio is directly obtained from JCF database.

8. **Liquidity ratio.** We use the ratio *Short Term Debt/ Long Term Debt*, which provides an idea of the firm's debt structure, as a measure of the firm's liquidity.

3.2 Methodology

In this paper, we try to identify the statistical factors explaining variance-covariance matrix of credit spread changes. This matrix is supposed to be decomposable into two elements: the covariance matrix of K common systematic factors and a matrix of idiosyncratic elements. These statistical factors are obtained by using principal component analysis (PCA) as advocated by Chamberlain and Rothschild (1983). To interpret these factors, we project onto the factorial axes some characteristics portfolios constructed as the Fama and French factors. The characteristics will be: volatility, stock momentum and equities' changes of financial ratios (coverage, leverage, profitability and liquidity ratios).

For the financial ratios, we match the accounting data changes for all fiscal yearends in calendar year t-1 (1999-2003) with the credit spread changes for January of year t to December of the same year t. In other words, we use the financial ratios changes of December of the year (t-1) to construct the portfolios for the period from January of year (t) to December of year (t). These portfolios are constructed by gathering the corporate bonds into classes of decreasing financial ratios values. These classes have a percentage of 10% (or 20%). For example, the first class of 10% includes corporate bonds of high accounting ratios.

Credit spread changes in the portfolios of each class are calculated by attributing the same weight to all corporate bonds. Then, we project these portfolios onto the factorial axes. If, for a given characteristic, the portfolios of the extreme classes have opposed-sign coordinates on a factorial axis and if the portfolios of classes are ordered according to this characteristic, this axis will be interpreted in terms of this characteristic. All portfolios are rebalanced at the beginning of each year.

For the volatility and stock momentum, we use the same technique. At the beginning of each year, the corporate bonds are ranked in descending order on the basis of their momentum and volatility factors.

4 Empirical Results and Interpretations

4.1 Number of factors explaining Credit Spread Changes

Using PCA on the universe of credit spread changes of 758 corporate bonds reveals the following results (Table 2):

Axis	1	2	3	4	5	6	7	8	9	10
Inertia (%)	43.1	13.8	8.4	7.8	4.1	2.7	2.2	1.8	1.5	1.3
Cumulative Inertia (%)	43.1	56.9	65.3	73.1	77.2	79.9	82.1	83.9	85.4	86.7

Table 2: Inertia explained by the first ten factorial axes

To determine the adequate number of factors that influence credit spread changes, we use the six criteria proposed by Bai and Ng (2002). These criteria are developed under the framework of large cross-sections and large time dimensions. Applying Bai and Ng (2002)'s criteria to our universe of credit spread changes, we find the following values (Table 3):

K	$PC_1(K)$	$PC_2(K)$	$PC_3(K)$	$IC_1(K)$	$IC_2(K)$	$IC_3(K)$
1	1784.81	1785.48	1782.98	7.55	7.55	7.54
2	1274.95	1276.29	1271.28	7.25	7.26	7.24
3	1068.36	1070.36	1062.85	7.10	7.11	7.09
4	964.66	967.33	957.31	7.02	7.03	7.01
5	905.97	909.31	896.78	6.97	6.98	6.95
6	874.36	878.36	863.34	6.96	6.96	6.93
7	864.72	869.39	851.86	6.95	6.95	6.92
8	906.11	911.44	891.41	7.03	7.04	7.00
9	899.01	905.02	882.48	7.03	7.04	6.99
10	904.28	910.95	885.91	7.04	7.05	7.00

Table 3: Number of factors based on Bai and Ng's criteria

According to Table 3, we observe that all criteria PC_k (1), PC_k (2), PC_k (3), IC_k (1), IC_k (2) and IC_k (3), suggest the presence of seven factors.

In this paper, we have just identified the first six statistical factors which explain 79.9% of credit spread changes.

4.2 Interpretation of the first six statistical factors

4.2.1 Interpretation of the first statistical factor

Similarly to the stock returns[8], where the most important factor is the equity market portfolio, we find here that the first statistical factor corresponds to the credit market index. In fact, the first statistical factor of credit spread changes is closely related to the US corporate bond spread changes, with a correlation coefficient of about 0.75.

Figure 1 illustrates the similarity of movements between the first statistical factor (centered and reduced) and the Global Broad Market Industrial Index spread changes (centered and reduced).

[8] See, for instance, Ben Hassine and Charpin (2005) and Ben Hassine (2005).

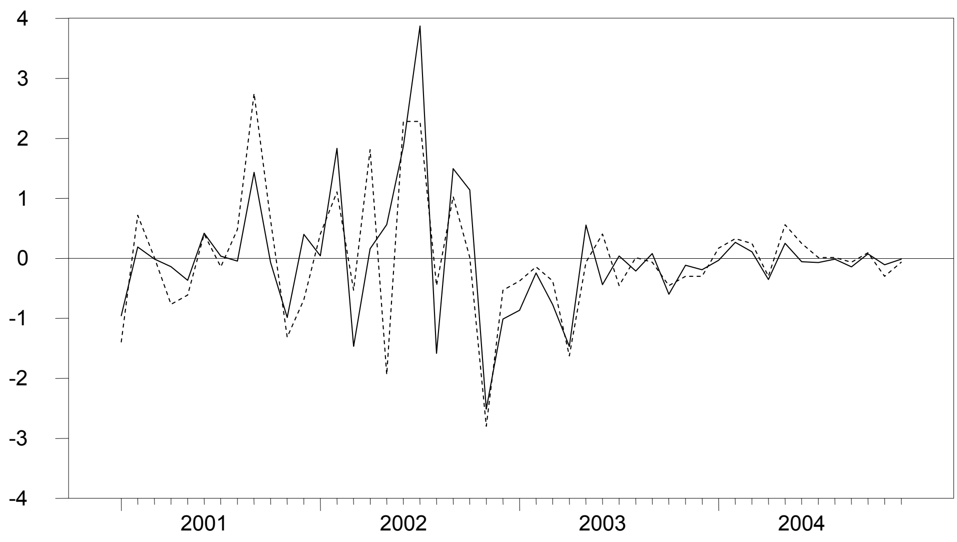

Figure 1: The first statistical factor (full line) and the Global Broad Market Industrial Index spread changes (dotted line)

To be able to interpret high-order factors, we will form portfolios based on a given characteristic such as volatility, stock momentum and accounting ratios changes (coverage, leverage, profitability and liquidity ratios). For that, we adopt an approach similar to that suggested by Fama and French (1992).

At the end of each year, the 758 corporate bonds are sorted according to the value of their financial ratio changes, volatility and stock momentum. Then, the bonds are distributed according to classes representing each one 10% of the total sample. For each class, we calculate the credit spread changes portfolios by attributing the same weight to all corporate bonds. These portfolios are then projected onto the factorial axes. The observation of these projections can possibly lead us to re-examine the percentage of the classes, by gathering consecutive classes whose projections are close.

4.2.2 Interpretation of the second statistical factor

The projections of equal-weighted portfolios sorted by decreasing volatility are ordered along the second factorial axis, as shown by table 4. Furthermore, table 4 indicates that the first class (which includes bonds of high volatility) has a negative coordinate on the second axis (-18.83), while the last class (which includes bonds of low volatility) has a positive coordinate on the second axis (0.94).

Sorting by decreasing volatility	Class 1 10%	Class 2 20%	Class 3 10%	Class 4 10%	Class 5 20%	Class 6 20%	Class 7 10%
Equal-weighted	-18.83	-9.07	-7.41	-6.21	-3.16	-2.57	0.94

Table 4: Coordinates of portfolios constructed according to the volatility on the 2nd factorial axis

Figure 2 plots the position of the different portfolios sorted by volatility (indicated by black squares) and clearly shows that the extreme classes' present opposed-sign coordinates on the second factorial axis. This figure shows that an increase in the volatility increases the credit spread changes.

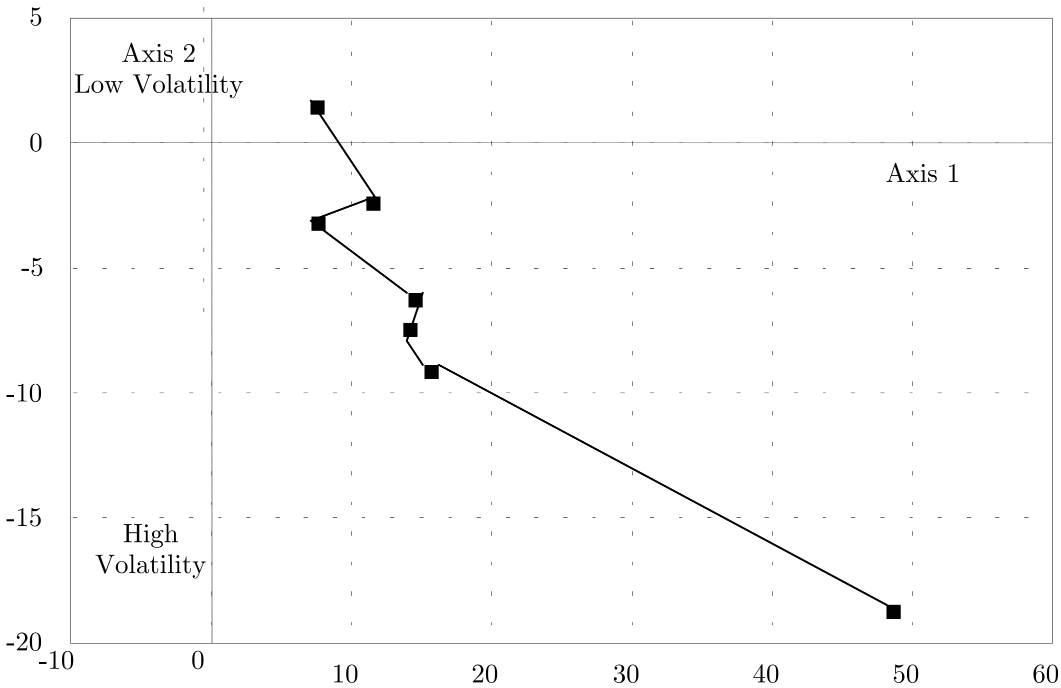

Figure 2: Projections of portfolios constructed according to volatility onto the 1st and 2nd axes

Moreover, table 5 gives some descriptive statistics of the 7 portfolios ranked by decreasing volatility. We observe that the corporate bonds with the highest volatility have a standard deviation of 58 basis points, while bonds with the lowest volatility have a 8.37 basis points standard deviation.

Classes	Mean (Bps)	Std Error (Bps)
Class1	-11.050718	58.988626
Class2	-3.277686	20.642556
Class3	-1.700110	20.497410
Class4	-0.916667	18.177503
Class5	-2.563734	12.145916
Class6	-1.887884	11.676099
Class7	-1.615616	8.378418

Table 5: Descriptive Statistics for portfolios ranked by decreasing volatility

Hence, the second factorial axis seems to oppose corporate bonds with low volatility to corporate bonds with high volatility.

4.2.3 Interpretation of the third statistical factor

Let us consider the third factorial axis. Tables 6 and 7 give the coordinates on axis 3 of portfolios constructed according to Net Debt changes and Net Debt / (Market Value of Equity + Net Debt) ratio changes, respectively. Focusing on these following two tables, we observe clearly that on the 3^{rd} factorial axis, the portfolios ranked on the basis of their corresponding equity leverage ratios changes are ordered according to decreasing values. Furthermore, the tables 6 and 7 show that the extreme classes' present opposed-sign coordinates on the fourth factorial axis. For example, the table 6 indicates that the top quintile has a positive coordinate (3.98), while the bottom quintile has a negative coordinate (-9.56).

Sorting by decreasing Net Debt changes	Class 1 20%	Class 2 20%	Class 3 10%	Class 4 10%	Class 5 20%	Class 6 20%
Equal-weighted	3.98	2.73	2.35	-5.03	-6.81	-9.56

Table 6: Coordinates of portfolios constructed according to Net Debt changes on the 3^{rd} factorial axis

Sorting by decreasing Leverage ratio changes	Class 1 10%	Class 2 20%	Class 3 10%	Class 4 10%	Class 5 30%	Class 6 20%
Equal-weighted	3.52	2.86	-1.51	-6.97	-8.89	-11.37

Table 7: Coordinates of portfolios constructed according to Leverage ratio changes on the 3^{rd} factorial axis

Figure 3 illustrates the projections of portfolios constructed according to Net Debt changes onto the factorial space (1,3). These portfolios are indicated by black squares and connected to each other. In general, this figure shows that when leverage ratios changes decrease, the credit spread changes decrease. In fact, according to the structural framework, the lower the leverage ratio, the more the firm's financial situation is improved.

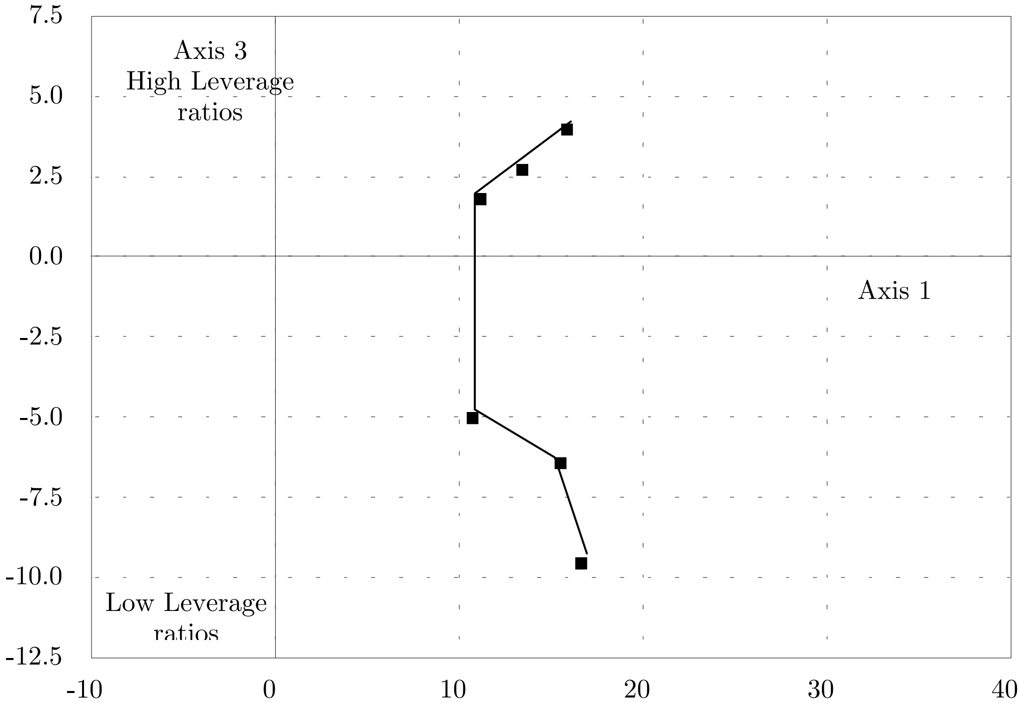

Figure 3: Projections of portfolios constructed according to Net Debt changes onto the 1st and 3rd axes

Therefore, we can advance that the third factorial axis opposes corporate bonds with low leverage ratios changes to corporate bonds with high leverage ratios changes.

4.2.4 Interpretation of the fourth statistical factor

Projecting portfolios ranked on the basis of the two coverage ratios onto the fourth factorial axis reveals a decreasing order along this axis. Indeed, tables 8 and 9 show that the extreme classes' present opposed-sign coordinates on the fourth factorial axis. For portfolios sorted by EBITDA interest, the top quintile has a negative coordinate (-1.89), while the bottom decile has a positive coordinate (6.24). For portfolios sorted by Net

Operating Cash Flow/Net Debt, the first class has a negative coordinate (-3.26), while the last class has a positive coordinate (3.95).

Sorting by decreasing EBITDA-interest	Class 1 20%	Class 2 30%	Class 3 10%	Class 4 10%	Class 5 10%	Class 6 10%	Class 7 10%
Equal-weighted	-1.89	-0.77	-0.02	0.30	0.79	1.54	6.24

Table 8: Coordinates of portfolios constructed according to EBITDA interest coverage on the 4^{th} factorial axis

Sorting by decreasing NOCF/Net Debt	Class 1 20%	Class 2 20%	Class 3 20%	Class 4 30%	Class 5 10%
Equal-weighted	-3.26	-1.18	0.44	2.36	3.95

Table 9: Coordinates of portfolios constructed according to NOCF/ Net Debt on the 4^{th} factorial axis

Thus, the fourth factorial axis seems to oppose corporate bonds with low coverage ratios changes to corporate bonds with high coverage ratios changes.

4.2.5 Interpretation of the fifth statistical factor

The projections of portfolios ranked on the basis of the profitability ratio changes onto the fifth factorial axis reveal a decreasing order among this axis. Table 10 provides that the extreme classes' present opposed-sign coordinates on the fifth factorial axis. In fact, the top quintile has a positive coordinate (5.81), while the bottom decile has a negative coordinate (-4.28).

Sorting by decreasing net margin	Class 1 20%	Class 2 20%	Class 3 20%	Class 4 20%	Class 5 10%	Class 6 10%
Equal-weighted	5.81	3.25	2.06	1.09	-2.74	-4.28

Table 10: Coordinates of portfolios constructed according to net margin on the 5^{th} factorial axis

Figure 4 plots the position of the different portfolios sorted by **Net Margin** changes (indicated by black squares). This figure confirms, in general, the sense of the theoretical relation between profitability ratios and the credit spread changes increase: an increase in profitability ratios may decrease the credit spread changes.

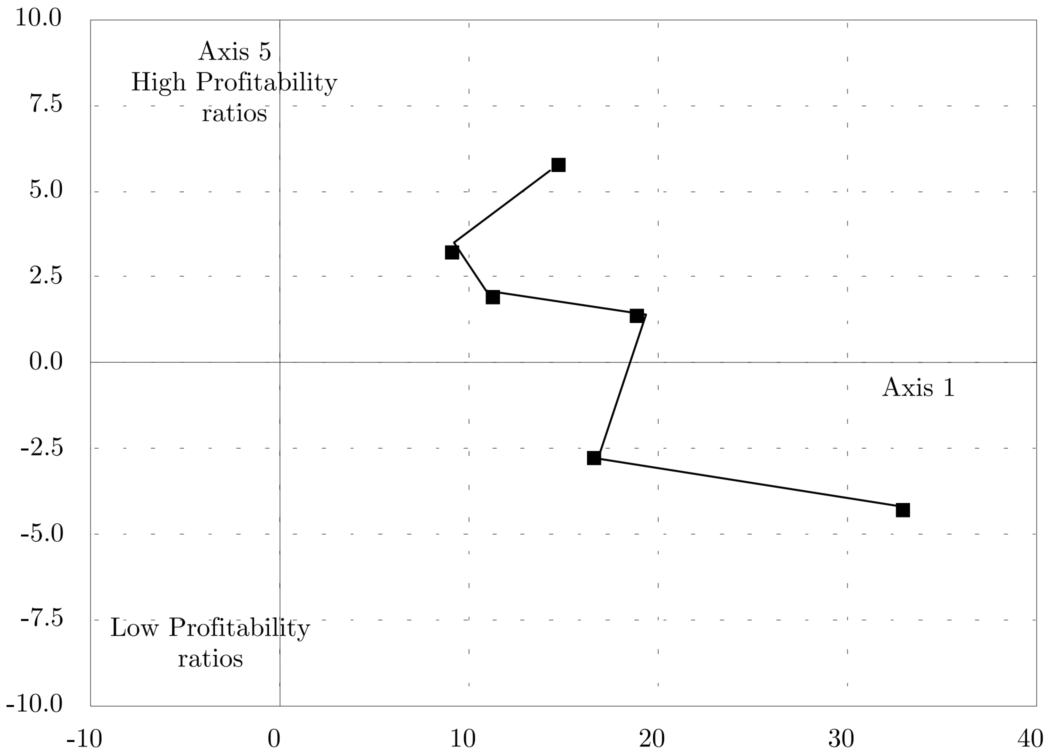

Figure 4: Projections of portfolios constructed according to profitability (NET MARGIN) ratios changes onto the 1st and 5th axes

For the liquidity ratio, we find an order of coordinates of the different portfolios constructed according to changes of this ratio on the 5th factorial axis, which are reported in the following table (table 11):

Sorting by decreasing liquidity ratio	Class 1 10%	Class 2 10%	Class 3 20%	Class 4 20%	Class 5 20%	Class 6 20%
Equal-weighted	5.82	3.54	2.59	-0.16	-1.64	-3.08

Table 11: Coordinates of portfolios constructed according to liquidity ratio changes on the 5th factorial axis

Figure 5 illustrates the projections of portfolios constructed according to liquidity ratio changes onto the factorial space (1,5). These portfolios are indicated by black squares and connected to each other.

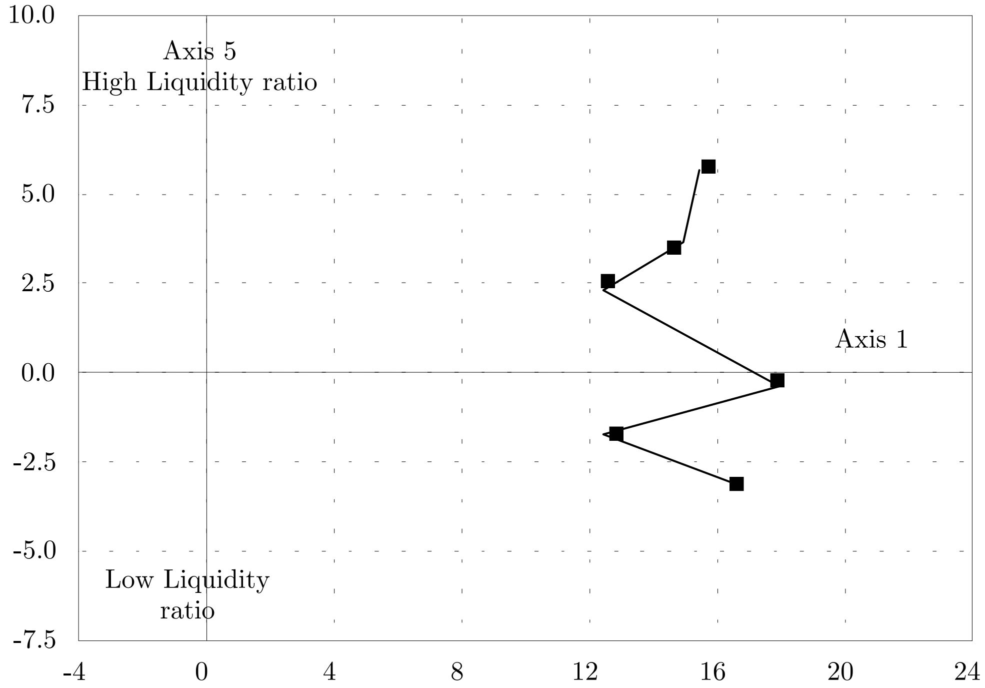

Figure 5: Projections of portfolios constructed according to liquidity ratio onto the 1st and 5th axes

According to table 11, the liquidity ratio seems also to characterize the fifth statistical factor. Hence, the fifth factorial axis can be associated with profitability and liquidity ratios changes.

4.2.5 Interpretation of the sixth statistical factor

Let us consider the sixth factorial axis. Table 12 gives the coordinates on axis 6 of portfolios constructed according to stock momentum. Focusing on this table, we observe clearly that on the 6th factorial axis, the portfolios ranked on the basis of their corresponding equity stock momentum are ordered according to decreasing values. Furthermore, the table 12 indicates that the extreme classes' present opposed-sign coordinates on the sixth factorial axis. For example, the top quintile has a positive coordinate (1.80), while the bottom quintile has a negative coordinate (-3.06).

Sorting by decreasing Stock momentum	Class 1 20%	Class 2 20%	Class 3 10%	Class 4 30%	Class 5 20%
Equal-weighted	1.80	1.02	0.54	-0.49	-3.06

Table 12: Coordinates of portfolios constructed according to stock momentum on the 6th factorial axis

Furthermore, figure 6 shows that the higher momentum in equity returns implies lower risk and consequently reduces spread changes. According to the structural framework, this result seems evident since increasing the momentum factors causes an increasing of future firm valuation, and could potentially imply lower probability of default and lower spread. Thus, axis 6 can be interpreted as an axis opposing corporate bonds with high stock momentum to corporate bonds with low stock momentum.

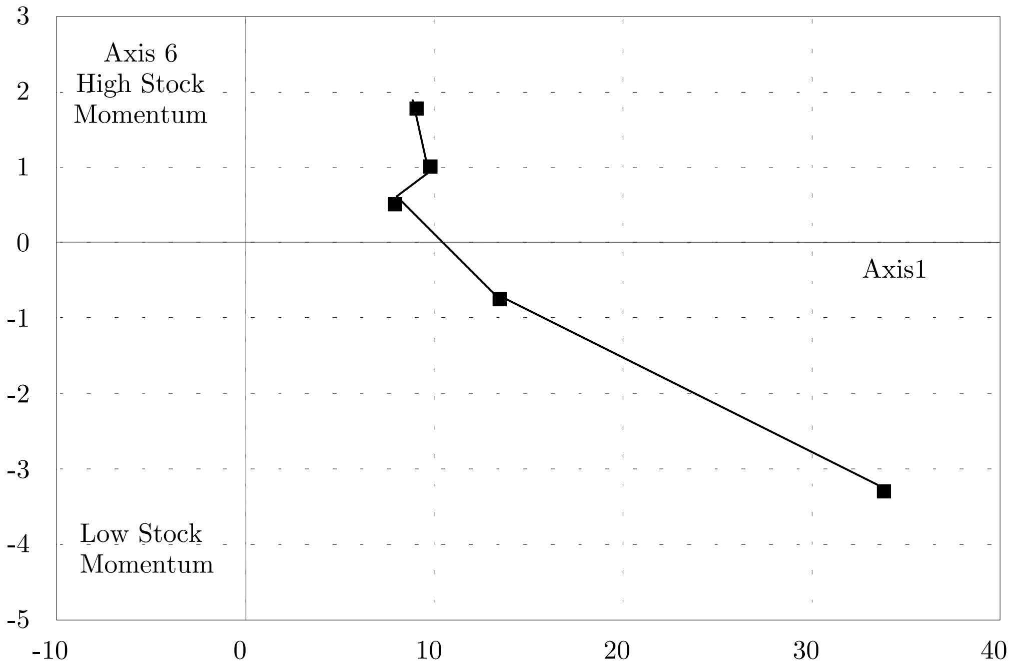

Figure 6: Projections of portfolios constructed according to stock momentum onto the 1st and 6th axes

It is important to note that the momentum factors play a significant role in explaining stocks returns and they have been used for 3 decades by most analysts and investors. In fact, an extensive body of empirical research documents that the cross-section of equity returns is predictable based on past returns. For example, Jegadeesh and Titman (1993) show that over an intermediate horizon of three to twelve months, past winners on average continue to outperform past losers, thus generating momentum in stock prices. However, there are few empirical studies on credit spread changes which use momentum factors. For example, Avramov, Jostova and Philipov (2004) use stock return momentum as a potential determinant of credit spread changes. They find that the bond spread respond to this momentum variable at the 10% level.

5 Summary and Conclusions

It is normally argued that factors derived from statistical methods such as Principal Components Analysis possess no financial or economic interpretation. Yet this paper shows that the first six factors, derived from a principal components analysis method suggested by Chamberlain and Rothschild (1983) and applied to changes in corporate credit spread of the US industrial sector, actually do have an interpretation. Our methodology is based on projecting on the factorial axes some characteristics portfolios constructed as the Fama and French factors.

Specifically, the US industrial market index is the most important driver of credit spread changes in the US industrial sector. Volatility equity seems to be the second strongest determinant of credit risk changes. The third statistical factor corresponds to leverage ratios. The fourth factor corresponds to coverage ratios. The fifth factorial axis corresponds conjointly to profitability and liquidity ratios. Stock momentum, which is mainly used in equity returns pricing, indeed do a good job of explaining credit spread changes.

Hence, this study shows a direct relationship between statistical factors explaining credit spread changes and a firm's fundamental variables and equity market factors. We provide empirical evidence for this link by showing that equity market factors (equity volatility and stock momentum factor) influence the changes in credit spread. So, this result is not consistent with the findings of Collin et al. (2001) who argue that "changes in credit spread are, to a great extent, driven by factors not associated with either the equity or Treasury markets".

The major contribution of our analysis is the construction of factors which are related to many components: the third factor is composed of two types of leverage ratios, the fourth factor is composed of two kinds of coverage ratios and the fifth factor is composed of two categories of financial ratios: profitability and liquidity ratios.

In addition, our analysis provides the relative importance of each factor found in the principal components analysis, through the percentages of inertia. Thus, the accounting ratios effect appears less significant than the volatility effect, and momentum effect appears less important than the financial ratios effects.

In sum, this paper shows that the PCA affords us an opportunity to study both the number and the nature of the factors driving credit spread changes. It also proves that equity market factors help explain individual bond credit spread changes.

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