Credit Risk and Market Risk: Analyzing US Credit Spreads

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Abstract

We attempt to disentangle US credit spreads' evolution into a part resulting from market risk influence and a part resulting from default risk influence. We consider two kinds of data, namely credit spreads (versus Treasury yields) as a proxy of credit risk and S&P 500 stock index as a proxy of market/systematic risk. Such data allow for achieving a sensitivity study of credit risk to systematic risk relative to sector, credit rating and maturity risk levels. First, we extract the common unobserved component of credit risk (i.e., common latent factor) from observed credit spread data in the light of three risk dimensions, namely credit rating, maturity and industry. We exhibit then the sensitivity of credit risk to market risk according to three different risk levels, namely the three risk dimensions previously mentioned. Second, we investigate the link prevailing between the common latent factor and S&P 500 stock index along with those three risk dimensions. We exhibit therefore the link prevailing between the systematic component of credit spreads (i.e., credit risk) and S&P 500 index as a proxy of market risk factor. We find that employing S&P 500 stock index as a proxy of the systematic risk component in US credit spreads generates a valuation bias while assessing credit risk.

Keywords: Credit spreads, Credit risk, Flexible least squares, Kalman filter, Latent factor, Market risk, Systematic risk.

JEL Codes: C32, C51, G1.

1 Introduction

Recent literature focuses on the basic components of credit risk, and mainly the interaction between systematic and idiosyncratic risk in determining credit risk level (see Crouhy, Galai & Mark (1999)). Namely, the influence of business cycle (that represents the systematic risk factor)[1] on credit risk is investigated while studying the impact of key macroeconomic indicators. On one hand, many authors investigated and emphasized the systematic nature and component of credit risk (see Jarrow & Turnbull (1995a,b), Das & Tufano (1996), Duffee (1998), Jarrow & Turnbull (2000), Elton, Gruber, Agrawal & Mann (2001), Hillegeist *et al.* (2002), Bongini *et al.* (2002), Allen & Saunders (2003), Xie, Wu & Shi (2004), Koopman, Lucas & Klaassen (2005), Dionne *et al.* (2006)). The obtained results support the significant role of both systematic risk and relevant market and/or macroeconomic indicators in explaining the level and evolution of credit risk fundamentals. On the other hand, other authors disentangled credit risk into two components such as systematic/market risk and idiosyncratic/specific risk (see Dichev (1998), Wilson (1998), Nickell et al. (2000), Baraton & Cuillere (2001), Crouhy, Galai & Mark (2000, 2001), Delianedis & Geske (2001), Spahr *et al.* (2002), Ericsson & Renault (2003), Gatfaoui (2003), Aramov *et al.* (2004), Gatfaoui (2005), Jarrow, Lando & Yu (2005), Bakshi, Madan & Zhang (2006)). Related issues support that credit risk results from the combination of financial and macroeconomic risk factors (i.e., market and systematic risk factors) with idiosyncratic and firm-specific risk factors (e.g., liquidity risk).[2]

More recently, various sophisticated latent factor models arose to study the relationship prevailing between credit risk and market risk, or equivalently business cycle (see Galgliardini & Gouriéroux (2004), Koopman, Lucas & Daniels (2005)). One-factor models attempt to account for the market risk side while assessing credit risk (see Cipollini & Missaglia (2005),

[1] Indeed, the systematic risk factor is usually represented by business conditions since this one is highly correlated with macroeconomic fundamentals (see Fama & French (1989) for example).

[2] See Ericsson & Renault (2003) as well as Driessen (2005) for example.

Hamerle, Liebig & Scheule (2004)) whereas multi-factor models focus on observed and unobserved latent macroeconomic factors (i.e., business cycle) underlying credit risk evolution (see Hui, Lo & Huang (2003), Tasche (2005), Berardi & Trova (2005)). Indeed, incorporating latent factors improves model accuracy and reliability while assessing credit risk (see Amato & Luisi (2006), Jakubik (2006)). With regard to corporate bonds and credit spreads, Elizalde (2005) shows that credit risk results essentially from common risk factors that affect all firms. Credit risk is decomposed into different unobservable factors among which a single common factor accounts for more than 50% of firm credit risk levels. Moreover, this single common factor is strongly correlated with known US stock market indices. In the same line, Saita (2006) implements a reduced-form latent factor model while studying credit spreads versus risk-free rates. The model incorporates macroeconomic variables as well as firm-specific factors such as leverage and firm volatility. This way, the author shows that expected excess returns on corporate bonds (i.e., credit spreads) depend on systematic risk factors. Namely, unknown and unobserved systematic risk factors in addition to Fama & French (1993) systematic risk factors might explain a large portion of observed credit spreads (i.e., default timing and default event). Studying also corporate bond spreads, Frühwirth, Schneider & Sögner (2005) distinguish between interest rate risk, credit risk (i.e., issuer-specific risk) and liquidity risk (i.e., bond-specific risk). These components are extracted from relevant latent processes that represent both bond-specific and issuer-specific risk factors. Moreover, the correlation between the risk-free term structure and credit risk is also taken into account. Later Berndt, Lookman & Obrega (2006) investigate the link between default risk premia and both systematic observed risk factors and an unobserved latent risk factor. Considering unexplained returns (i.e., that part of corporate bond returns, which does not result from changes in risk-free rates and expected losses), they distinguish between Fama & French (1993) systematic factors (e.g., default and term factors), Jegadeesh & Titman (1993) momentum factor, and an unobserved common latent component. Moreover, unexplained returns reveal to be independent of default probabilities, credit ratings, leverage ratios and recovery rates. With regard to failure rates, Koopman & Lucas (2005) employ a multivariate unobserved component methodology to investigate the link prevailing between macroeconomic conditions and both credit spreads and failure rates. They emphasize empirically the correlation existing between credit risk and macroeconomic state. In a similar view, Jakubik (2006) investigates the link between credit risk and business cycle. The author targets the impact of macroeconomic changes on default events. For microeconomic reasons, the author considers macro credit risk models that incorporate latent systematic risk factors in order to predict default rates.

In the light of the strong relationship between credit risk and market risk, we realize a two-stage study while investigating US credit spreads' evolutions. First, we emphasize the global common component in all credit spreads under consideration, which represents the systematic part of credit risk at sector-, rating-, and maturity-based levels. We argue that the decomposition of credit spreads into systematic and idiosyncratic components varies across sectors, credit ratings and maturities. Second, we investigate the dynamic link that prevails between the systematic component in credit spreads and the S&P 500 stock index return. We check whether the common practice that resorts to S&P 500 stock market index as a proxy for systematic risk factor is coherent. Specifically, we address three distinct questions. Firstly, can we describe the interaction arising between credit risk and market risk over time? Secondly, is S&P 500 index a convenient proxy for the financial market when assessing the systematic component of US credit spreads? Thirdly, when this is not the case, can we use the link prevailing between credit spreads and S&P 500 index to extract or estimate the systematic part of credit spreads?

The paper is organized as follows. Section 2 introduces the data and some related empirical features. Section 3 presents the methodology employed to extract the common latent component in credit spreads in the light of three risk dimensions, namely economic sector, credit rating and maturity. Section 4 investigates the link between the common latent component in credit spreads and S&P 500 stock index along with the three previous risk dimensions. Finally, section 5 draws some concluding remarks and proposes future research extensions.

2 Data

We introduce the set of data under consideration as well as related time horizon and specific exhibited features.

2.1 Description

We consider monthly data ranging from May 1991 to November 2000, namely a total of 115 observations per series. Those data are extracted from Bloomberg database, and consist of US corporate credit spreads and S&P 500 stock market index. US corporate credit spreads are expressed in basis points. First, credit spreads are computed as the difference between middle aggregate risky bond yields and corresponding Treasury yields. They are sorted by sector, rating and maturity. Indeed, we consider four different sectors, namely banking and finance (BF), industrials (IN), power (PW) and telecommunications (TL). Moreover, we focus on investment grade risky bonds whose ratings range from AAA to BAA, and are provided by Moody's rating agency. Maturities range from one year to twenty years (when they are available) in order to study short term and long term credit risk profiles. We therefore consider a total number of 116 credit spread time series all sectors, maturities and ratings included. The whole set of average corporate credit spreads under consideration is listed in table 1.

We focus therefore on the economic trend in US corporate credit spreads along with three levels of analysis, namely industry, credit rating and maturity. Those three risk level analyses are motivated by empirical findings. Industry distinction is motivated by both the fact that firm characteristics vary across sectors (see Collin-Dufresne & Goldstein (2001)) and the existence of industry-specific fundamentals (see Wilson (1997a,b)). Credit ratings exhibit a strong informational content (see Boot, Milbourn & Schmeits (2006) and Odders-White & Ready (2006)). Namely, credit ratings express an issuer's solvency along with macroeconomic risk, commercial risk (e.g., competitive environment, firm positioning) and financial state (e.g., financial policy and structure, financial flexibility, profitability) concerns. Indeed, Boot, Milbourn & Schmeits (2006) emphasize the substantial and significant economic role of credit ratings (i.e., signalling role about firm quality as well as related creditworthiness for potential investors, and monitoring process of rating agencies) insofar as firms need to act in order to maintain and/or improve their credit rating. Moreover, credit ratings impact strongly firms' debt levels as well as related capital structures (see Faulkender & Petersen (2005) and Kisgen (2006)). Specifically, Kisgen (2006) shows the immediate impact of credit ratings on firms' capital structure decisions. Incidentally and with regard to credit risk term structure, firm-specific factors as well

Table 1: Coporate credit spreads

Rating	*Maturity (years)*							
	1	**2**	**3**	**4**	**5**	**7**	**10**	**20**
AAA	IN BF	IN BF	BF	IN	IN BF	IN BF	IN BF	IN
AA2	IN BF PW	IN BF	IN BF		IN BF PW	IN BF PW	IN BF PW	
AA3	IN TL PW	IN TL PW	IN TL	TL	IN TL PW	IN TL PW	TL PW	
A1	IN TL PW	IN TL	IN TL		IN TL PW	IN TL PW	IN TL	
A2	IN TL PW	IN TL PW	IN TL		IN TL PW	IN TL PW	IN TL PW	
A3	IN TL PW	IN TL PW	IN TL		IN TL PW	IN TL PW	TL	
BAA1	IN TL	IN TL	IN TL		IN TL	IN TL	IN TL	
BAA2	IN	IN	IN		IN		IN	
BAA3	IN	IN	IN		IN	IN	IN	

as corresponding country's financial system and institutional traditions (i.e., regulations and corporate governance) determine the debt maturity structure of a firm (see Antoniou, Guney & Paudyal (2006)). Antoniou, Guney & Paudyal (2006) show a negative link between debt maturity and firm liquidity. Specifically, those authors identify market related factors that impact substantially any firm's debt maturity structure. Moreover, Shimko, Tejima & Van Deventer (1993) show that the slope of credit spread term structure (as well as credit spread volatility) depends on the changes in interest rate volatility (i.e., link with some market-specific fundamental).

Second, we consider the Standard & Poor's composite index (S&P 500) as a proxy of market/systematic risk factor (i.e., some market portfolio with five hundreds stocks). Since credit spreads exhibit some yield nature and for homogeneity purposes, we consider the continuous monthly returns of S&P 500 index rather than its levels. Namely, according to Fisher (1959), corporate credit spreads and S&P 500 stock index (which is also thought as a proxy of business conditions) should be negatively linked (see also Gatfaoui (2005,2006)) given that we lie in the growth side of the business cycle.[3] To check for the coherency of our homogeneity concern, we naively computed the non-parametric correlation coefficients (i.e., Kendall's tau and Spearman's rho) between US corporate credit spreads and both S&P 500 levels and S&P 500 continuous returns. In unreported results, we found a general positive link[4] between US corporate credit spreads and S&P 500 levels whereas we found a strong negative link[5] between US corporate credit spreads and S&P 500 returns. Consequently, our homogeneity concern has a high significance all the more that it impacts the nature of the results to be obtained as well as related interpretation and conclusions.

2.2 Empirical features

We underline and exhibit some statistical features of the data under consideration. First, in unreported results, we ran a Phillips & Perron stationarity test at a one percent level and found that S&P 500 index returns are

[3] Generally speaking, this negative link means that an increase of systematic risk impacts negatively credit risk. Specifically, a decrease in S&P 500 returns generates a widening of corporate credit spreads.

[4] An extremely small number of computed non-parametric correlation coefficients are negative.

[5] All the non-parametric correlation coefficients that were computed are negative.

Table 2: Median industrial credit spreads in basis points

	1Y	2Y	3Y	4Y	5Y	7Y	10Y	20Y
AAA	38.0000	32.0000		30.0000	32.0000	31.0000	34.0000	35.0000
AA2	44.0000	37.0000	36.5000		37.0000	38.0000	40.0000	
AA3	49.0000	40.0000	41.0000		40.0000	42.0000		
A1	56.0000	46.0000	50.0000		49.0000	50.0000	53.0000	
A2	64.0000	52.0000	56.5000		63.0000	63.0000	64.0000	
A3	73.0000	61.0000	62.5000		69.0000	68.0000		
BAA1	84.0000	77.0000	74.5000		78.0000	79.0000	80.0000	
BAA2	93.0000	85.0000	82.5000		85.0000		89.0000	
BAA3	109.0000	99.0000	96.5000		97.0000	111.0000	118.0000	

Table 3: Skewness of industrial credit spreads

	1Y	2Y	3Y	4Y	5Y	7Y	10Y	20Y
AAA	0.0054	0.5061		1.5554	1.7469	1.9563	1.7289	1.5088
AA2	0.6544	0.6393	1.1702		1.9193	2.0665	1.7625	
AA3	0.6825	0.5117	0.8781		1.6205	1.8942		
A1	0.7014	0.4280	0.4542		1.2040	1.5011	1.3681	
A2	0.4606	0.4594	0.3972		0.8440	1.4213	1.3343	
A3	0.3265	0.2956	0.4108		0.9510	1.3384		
BAA1	0.3486	0.2885	0.3299		0.7359	1.0474	1.1591	
BAA2	0.2805	0.1336	0.2475		0.5195		1.0095	
BAA3	0.5921	0.4957	0.4105		0.3317	0.4640	0.4953	

stationary whereas US corporate credit spreads are non-stationary. Specifically, credit spreads reveal to be first order integrated time series. Second, we computed some descriptive statistics such as median, skewness and kurtosis for our credit spreads and S&P 500 stock index. Related results are displayed for each sector and listed in tables 2 to 14.

We therefore consider asymmetric and non-normal data. As regards S&P 500 index return, this stock market index return is positively skewed and exhibits a positive excess kurtosis as compared the ones of the Gaussian distribution. As regards US corporate credit spreads, they exhibit the following statistical features whatever the credit spread under consideration. As functions of rating grades, median corporate credit spreads decrease when the corresponding credit rating improves. As functions of maturity, median cor-

Table 4: Excess kurtosis for industrial credit spreads

	1Y	2Y	3Y	4Y	5Y	7Y	10Y	20Y
AAA	-0.6695	-0.0700		2.6838	3.4048	4.3448	2.6663	1.9876
AA2	-0.2953	-0.4372	0.8140		3.6516	4.3380	2.8339	
AA3	-0.4172	-0.7691	-0.2185		2.2742	3.5721		
A1	-0.2116	-1.1199	-0.9971		1.0406	2.2640	1.7285	
A2	-0.6324	-1.0974	-1.0632		0.1875	2.0272	1.5532	
A3	-0.9194	-1.3706	-1.1146		0.3473	2.0272		
BAA1	-1.0692	-1.2390	-1.1264		-0.2857	0.5366	0.6907	
BAA2	-1.1085	-1.4962	-1.3784		-0.8617		0.2631	
BAA3	-0.7828	-0.9299	-1.1445		-1.3095	-1.0121	-0.8430	

Table 5: Median banking and finance credit spreads in basis points

	1Y	2Y	3Y	5Y	7Y	10Y
AAA	41.0000	36.0000	36.5000	39.0000	44.0000	46.0000
AA2	50.0000	42.0000	43.5000	50.0000	54.0000	55.0000

Table 6: Skewness of banking and finance credit spreads

	1Y	2Y	3Y	5Y	7Y	10Y
AAA	0.0771	0.5160	0.8497	1.0151	1.1624	0.9990
AA2	0.4046	0.6222	0.8230	1.2061	1.3692	1.3074

Table 7: Excess kurtosis for banking and finance credit spreads

	1Y	2Y	3Y	5Y	7Y	10Y
AAA	-0.0602	-0.4785	-0.1975	0.2643	0.6604	-0.1717
AA2	-0.4766	-0.6893	-0.4021	0.9498	1.2868	0.9199

Table 8: Median telecommunication credit spreads in basis points

	1Y	2Y	3Y	4Y	5Y	7Y	10Y
AA3	50.0000	40.0000	40.5000	38.0000	40.0000	42.0000	44.0000
A1	59.0000	49.0000	49.5000		46.0000	49.0000	52.0000
A2	63.0000	56.0000	54.0000		51.0000	54.0000	53.0000
A3	68.0000	61.0000	59.5000		56.0000	59.0000	59.0000
BAA1	74.0000	68.0000	67.0000		67.0000	66.0000	69.0000

Table 9: Skewness of telecommunication credit spreads

	1Y	2Y	3Y	4Y	5Y	7Y	10Y
AA3	0.1733	0.7575	1.3812	1.5304	1.7811	1.8314	1.8297
A1	0.0221	0.4899	1.1382		1.8101	1.8616	1.8088
A2	0.3913	0.5998	1.4356		1.9565	2.0339	1.8950
A3	0.0221	0.4899	1.1382		1.8101	1.8616	1.8088
BAA1	0.5030	0.4089	1.0116		1.5206	1.4555	1.4698

Table 10: Excess kurtosis for telecommunication credit spreads

	1Y	2Y	3Y	4Y	5Y	7Y	10Y
AA3	-0.8179	-0.2833	1.3247	2.2035	2.6105	3.0903	2.7696
A1	-0.9156	-0.2947	0.9891		2.8846	3.3375	2.8933
A2	-0.6124	0.2381	2.2776		3.6817	4.1023	3.3160
A3	-0.9156	-0.2947	0.9891		2.8846	3.3375	2.8933
BAA1	-0.6092	-0.7629	0.5492		2.0590	1.8260	1.8475

Table 11: Median power credit spreads in basis points

	1Y	2Y	5Y	7Y	10Y
AA2	45.0000		36.0000	40.0000	44.0000
AA3	55.0000	44.0000	41.0000	45.0000	47.0000
A1	62.0000		47.0000	50.0000	
A2	66.0000	52.0000	52.0000	55.0000	58.0000
A3	72.0000	57.0000	58.0000	62.0000	

Table 12: Skewness of power credit spreads

	1Y	2Y	5Y	7Y	10Y
AA2	0.3751		1.7064	1.8879	1.5682
AA3	0.0983	0.7859	1.7813	1.9007	1.5888
A1	0.0828		1.8710	1.9887	
A2	-0.0158	0.8360	1.7872	1.9017	1.7093
A3	0.0771	0.6016	1.7624	1.8828	

Table 13: Excess kurtosis for power credit spreads

	1Y	2Y	5Y	7Y	10Y
AA2	-0.3843		2.5288	3.2178	1.8704
AA3	-1.1282	0.0435	2.6298	3.3824	1.9500
A1	-1.0025		2.8878	3.6656	
A2	-1.0718	-0.0637	2.6025	3.2532	2.3077
A3	-0.8979	-0.5393	2.6901	3.2519	

Table 14: Descriptive statistics for Standard and Poor's 500 stock index

	Level	Return (bps)
Median	645.3000	83.7925
Skewness	0.6585	0.1873
Excess kurtosis	-1.0973	1.4405

porate credit spreads tighten until two-, three- or four-year maturities, and then widen as maturity increases. Such a behavior doesn't apply to telecommunication credit spreads whose behaviors are farther more irregular as functions of maturity. Moreover, corporate credit spreads are generally positively skewed (i.e., right-skewed, or equivalently with a fat right-tail). Hence, over our studied time horizon, we face substantial numbers of credit spreads lying above their related average values (i.e., substantial risk of high credit spreads as compared to their corresponding average levels). Finally and generally speaking, their corresponding excess kurtosis is usually negative for maturities below four years (below two years for the telecommunication sector) whereas it becomes positive for other higher maturities except for the lowest rating grades of industrial and power sectors.

3 Latent systematic factor

Recent literature employs observed macroeconomic variables to exhibit the correlation of default indicators across firms as well as industries (see Gersbach & Lipponer (2003)[6]). According to related empirical issues, macroeconomic factors reveal to be insufficient while assessing credit risk insofar as

[6] Those authors exhibit the impact of macroeconomic shocks on both default probabilities and default correlations. They find that default correlations may explain more than fifty percent of credit risk increase in case of adverse macroeconomic shocks.

additional latent risk factors need to be considered. To bypass such an issue, we gather any observed and unobserved common financial, economic and macro component describing credit risk fundamentals (e.g., credit spreads) into one global common unobserved latent factor. Our motivation comes from Collin-Dufresne *et al.* (2001) who show that credit spreads' changes are mainly driven by a common latent factor in corporate bonds. We then resort to a specific econometric tool to exhibit such a common latent component in corporate credit spreads, namely Kalman linear filter methodology.

3.1 Methodology

Kalman filter (see Kalman (1960), Brown & Hwang (1997), and Cressie & Wikle (2002)) is a state-space representation that allows for considering an unobserved variable (i.e., a state variable), which is estimated with the observable model (i.e., observed variables or measures). Specifically, Kalman filter attempts to estimate a state variable (e.g., the common latent component in credit spreads) given disturbed observations about the corresponding system (e.g., observed corporate credit spreads).[7] Indeed, observed measures (i.e., corporate credit spreads) are functions of the state variable (i.e., the state of the system, or equivalently the unobserved common component in corporate credit spreads) insofar as the considered measures are disturbed by a random noise called measurement noise. The main advantage is that such an econometric method can be applied to stationary as well as non-stationary data.[8] Moreover, we do not need a proxy for business conditions or systematic risk factor, this unobserved risk component being inferred from Kalman filter.

We consider that our state variable, namely the common latent component in credit spreads, follows a first order Markov process. And, we consider the following linear measurement equation (Equation 1) and state (i.e., dynamic/transition) equation (Equation 2):

$$CS_t = \alpha \cdot M_t + e_t \tag{1}$$

[7] More precisely, Kalman filter attempts to estimate the common latent component at each time t conditional on observed corporate credit spreads until time t. This methodology minimizes realized squared errors on the common latent component in credit spreads (i.e., quadratic minimization algorithm).

[8] Recall that S&P 500 index returns are stationary whereas corporate credit spreads are non-stationary.

$$M_t = \alpha_M \, M_{t-1} + w_t \tag{2}$$

with $CS_t = \begin{bmatrix} CS_t^1 \\ \vdots \\ CS_t^N \end{bmatrix}$, $\alpha = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix}$, and $e_t = \begin{bmatrix} e_t^1 \\ \vdots \\ e_t^N \end{bmatrix}$. First, N depends on the analysis level, namely sector-, rating- or maturity-based analysis,[9] and time t ranges from 1 to 115. Second, CS_t represents the set of credit spreads under consideration (i.e., observed variables/measure variables), α is a vector that represents the sensitivity of credit spreads to the common latent component M_t (i.e., state variable or hidden/unobserved variable), e_t is a measurement error that represents the unsystematic/idiosyncratic credit spread component, α_M is a state transition scalar and w_t is a state error (i.e., transition/dynamic error) that may represent market-specific anomalies or market-specific liquidity effects. Moreover, we assume that (e_t) and (w_t) are independent Gaussian white noises. Third, we consider a causal and invertible state-space model such that:

$$\begin{pmatrix} e_t \\ w_t \end{pmatrix} \backsim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} H_t & 0 \\ 0 & Q_t \end{bmatrix} \right)$$

and $M_0 \backsim N\left(m_0, P_0\right)$ where $N\left(\cdot\right)$ is the Gaussian distribution, m_0 and P_0 are known state expectation and variance parameters,[10] H_t is the measurement error covariance matrix and Q_t is the state variance parameter. Incidentally, we also assume a stationary setting such that α, α_M, H_t and Q_t are independent of time t (i.e., H_t and Q_t take the same value whatever the time point t under consideration). We furthermore make the following complementary assumptions. As a first step, state variance parameters P_0 and $Q_t = \sigma_M^2$ are set to take distinct and different values. As a second step, $H_t = Diag\left[\sigma_i^2\right]_{1 \leq i \leq N}$ is a diagonal $N \times N$ covariance matrix. Whatever the analysis level (i.e., sector, rating and industry), Kalman methodology allows then for decomposing

[9] At a sector level, N is successively 52, 12, 31 and 21 for IN, BF, TL and PW sectors respectively. At a rating level, N is successively 12, 5, 6, 15, 17, 15, 16, 17 and 13 for BAA1, BAA2, BAA3, A1, A2, A3, AA2, AA3 and AAA rating grades respectively. At a maturity level, N is successively 21, 19, 15, 2, 21, 20, 17 and 1 for 1, 2, 3, 4, 5, 7, 10 and 20-year maturities respectively.

[10] We emphasize the fact that M_0 is independent of both (e_t) and (w_t). Moreover, M_0 represents the initial state of the system, or equivalently the initial value of the common latent factor that we need to guess.

a set of credit spreads into a systematic latent component (i.e., common unobserved factor) and an idiosyncratic (i.e., unsystematic) component, which is peculiar to each credit spread under consideration in the light of the chosen analysis level.

Consequently, running our state-space representation requires the estimation of $2N + 4$ parameters, namely measure-specific sensitivity parameters α, state transition parameter α_M, initial value M_0 of the common latent component (i.e., initial state of the system), diagonal covariance matrix H_t composed of N elements, variance P_0 of the initial value of the common latent component, and state variance parameter σ_M^2. Under normality assumptions, CS_t follows a multivariate normal law conditional on M_t and past values of both latent factor M and related credit spreads CS. Therefore, implementing Kalman methodology leads to maximize the log-likelihood of the conditional distribution of CS_t.

Using Kalman filter methodology will then help make an inventory of and rank the sensitivity levels of credit spreads to the common latent component (i.e., unobserved systematic factor) as functions of credit rating, maturity and industry. Those sensitivity levels focus on the extent to which credit spreads tend to evolve together (i.e., the degree of instantaneous link or correlation) over time in the light of their respective industry, rating and maturity. Such a concern is of high significance for credit risk managers (see Wilson (1998)). Indeed, diversified credit portfolios usually bear the common risk component in their corresponding constituent credit risky assets. Since the idiosyncratic risk component of their credit portfolios is diversified away, credit risk managers focus on the related residual systematic risk component (i.e., correlation risk of credit risky assets or credit lines). Moreover, diversification needs to be envisioned in the light of asset-specific and sector-specific features among others.

3.2 Econometric results

We realize a three-stage study while trying to understand and highlight the common evolution trend that drives US corporate credit spreads. First, we investigate a common component in credit spreads at a sector level. For each sector, we extract the common systematic risk component in credit spreads while considering all available maturities and rating grades. We then exhibit the unobserved systematic risk component in sector credit risk. Second, we investigate a common component in credit spreads at a rating grade level. For each rating grade, we extract the common systematic risk component in credit spreads while considering all available maturities and sectors. We then exhibit the unobserved systematic risk component in credit risk as a function of rating grades. Third, we investigate a common component in credit spreads at a maturity level. For each maturity, we extract the common systematic risk component in credit spreads while considering all available sectors and rating grades. We therefore exhibit the unobserved systematic risk component in credit risk as a function of maturity.

We undertake our state-space model estimation while employing a Broyden-Fletcher-Goldfarb-Shano optimization algorithm. Corresponding relative gradients are computed with an accuracy level of 6 digits. Related significant Kalman results are given in the appendix. We just summarize briefly the obtained results. With regard to the sector level and whatever the industry under consideration, corresponding α estimates lie between 1.7 and 4 for BF, TL and PW sectors whereas they lie between 2 and 6 for IN industry. These estimates are all significant at a one percent Student test level for BF, TL and IN whereas they are significant at a ten percent test level for BF sector. The same conclusion applies to related standard deviations. Given that α estimates are positive and above unity, credit spreads tend then to magnify the shocks on the corresponding sector-specific common latent components over time (i.e., they magnify systematic sector-specific shocks). Moreover, Q_t, M_0 and α_M coefficients are significant for the corresponding respective Student test levels whereas P_0 is insignificant. With regard to the rating level and whatever the credit rating under consideration, corresponding α estimates lie between 1.6 and 5. These estimates as well as related standard deviations are all significant at a one percent Student test level except for A2 rating grade case whose significance level is five percent. Hence, credit spreads magnify the shocks on the related common latent component M_t as a function of credit rating grades (i.e., they magnify systematic rating-based shocks). Moreover, Q_t, M_0 and α_M coefficients are significant at a one percent Student test level whereas P_0 is insignificant. With regard to the maturity level and whatever the maturity under consideration, corresponding α estimates lie generally between 1.4 and 4 except for four- and twenty-year maturities for which these estimates lie between 5 and 6. These estimates as well as related standard deviations are all significant at a one percent Student test level. Then, credit spreads magnify the shocks on the related

Table 15: Descriptive statistics for sector-based common latent factors

	IN	BF	TL	PW
Median	10.0409	19.5821	21.9827	18.8570
Standard deviation	4.0155	8.2560	9.9231	9.0311
Skewness	0.2896	1.1041	1.7510	1.9027
Excess kurtosis	-1.3149	0.2772	2.8277	3.0994

Table 16: Descriptive statistics for rating-based common latent factors

Rating	Median	Standard deviation	Skewness	Excess kurtosis
AAA	15.9781	7.0866	1.3159	0.9249
AA2	16.2693	6.8280	1.4483	1.5218
AA3	19.5355	9.9622	1.8304	2.7864
A1	20.0947	8.5697	1.6270	2.3761
A2	26.9554	10.5694	1.4620	2.0131
A3	23.3196	8.7974	1.2459	1.2935
BAA1	27.1664	10.4231	0.9789	0.3716
BAA2	18.1252	7.2284	0.2289	-1.4101
BAA3	30.6017	13.0718	0.3255	-1.3107

common latent component M_t as a function of maturity (i.e., they magnify systematic maturity-based shocks). Moreover, Q_t, M_0 and α_M coefficients are significant at a one percent Student test level whereas P_0 is insignificant.

The results we get with regard to common latent components in corporate US credit spreads as functions of credit rating, maturity and industry are listed below from table 15 to table 17.

The median sector-specific common latent factor (i.e., the median value of the systematic sector-specific part in credit spreads, or equivalently the median value of the common latent factor in credit spreads that is peculiar to each sector) is the highest for TL sector and the lowest for IN sector. Sector-specific common latent factors (i.e., systematic sector-specific components in credit spreads) are all positively skewed and exhibit generally a positive excess kurtosis except for IN systematic factor (i.e., IN common latent factor).

The median rating-based common latent factor (i.e., the median value of

Table 17: Descriptive statistics for maturity-based common latent factors

Maturity	Median	Standard deviation	Skewness	Excess kurtosis
1Y	30.0761	11.8101	0.2860	-1.3189
2Y	22.1591	8.1722	1.1645	1.0397
3Y	13.0737	4.7913	0.9922	0.1687
4Y	9.5369	3.9492	1.3082	1.1095
5Y	22.7591	9.3145	1.3937	1.4712
7Y	18.7156	9.4556	1.9680	3.5429
10Y	15.0847	7.0048	1.8651	2.9549
20Y	9.3821	6.0739	1.5973	1.9725

the systematic rating-based part in credit spreads, or equivalently the median value of the common latent factor in credit spreads that is peculiar to each credit rating grade) is the highest for BAA3 grade and the lowest for AAA grade. Moreover, median values of rating-based common latent factors in credit spreads are a non-monotonous function of rating grades. Rating-based common latent factors (i.e., systematic rating-based components in credit spreads) are all positively skewed and exhibit generally a positive excess kurtosis except for BAA3 and BAA2 systematic factors (i.e., BAA3 and BAA2 common latent factors).

The median maturity-based common latent factor (i.e., the median value of the systematic maturity-based part in credit spreads, or equivalently the median value of the common latent factor in credit spreads that is peculiar to each maturity) is the highest for one-year maturity and the lowest for twenty-year maturity. Moreover, median values of maturity-based common latent factors in credit spreads are a non-monotonous function of maturity. However, short term/medium and long term credit spreads exhibit a higher/lower systematic maturity-based component respectively.[11] Maturity-based common latent factors (i.e., systematic maturity-based components in credit spreads) are all positively skewed and exhibit generally a positive excess kurtosis except for the one-year systematic factor (i.e., the one-year common latent factor).

[11] In unreported results, we notice that the one-year systematic factor in credit spreads exhibits generally the highest level over time whereas both four-year and twenty-year systematic factors in credit spreads behave globally in the same way and exhibit the same levels over time.

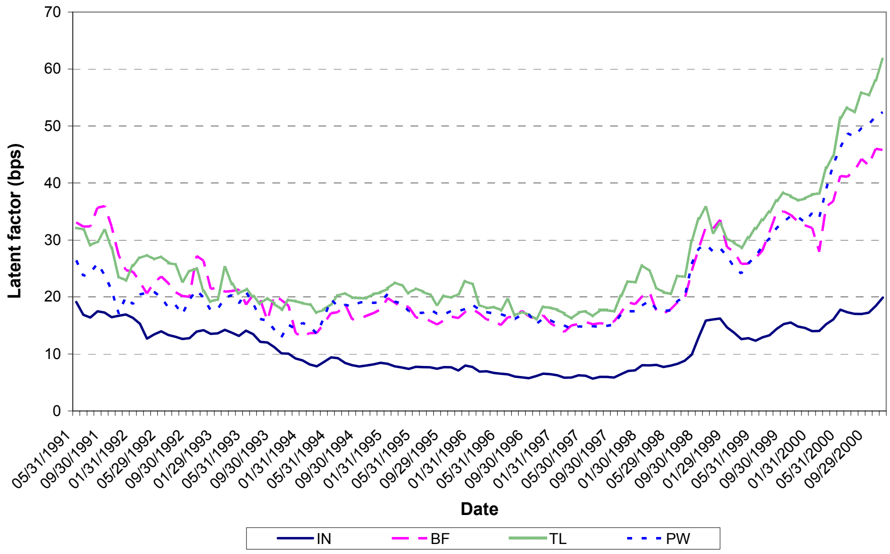

Figure 1: Sector-specific common latent factors in credit spreads

To get a general view, we also plot the levels of the common latent factors we obtained after running Kalman filter as functions of sector, credit rating and maturity (see figures 1 to 3).

Previous plots summarize the preliminary results displayed in tables 15 to 17. First, IN sector exhibits the lowest systematic credit spread component over time (i.e., lowest sensitivity to market risk at a sector level) whereas TL sector usually exhibits the highest one as compared to other sector-specific systematic credit spread components. Second, BAA3 systematic credit spread component is generally the highest over our time horizon (i.e., highest sensitivity to market risk at a credit rating level). Until 1994, AAA and AA2 systematic credit spread components are the lowest whereas BAA2 systematic credit spread component becomes generally the lowest after 1994 as compared to other rating-based systematic credit spread components. Third, the one-year systematic credit spread component is generally the highest over our time horizon (i.e., highest sensitivity to market risk at a maturity level). Until 1997, both four-year and twenty-year systematic credit spread components are the lowest whereas only twenty-year systematic credit spread component remains the lowest after 1997 as compared to

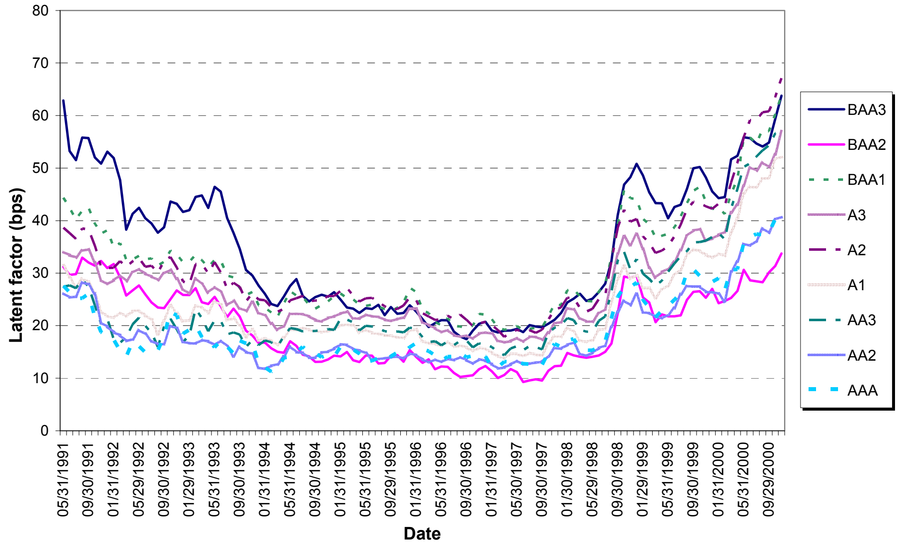

Figure 2: Rating-based common latent factors in credit spreads

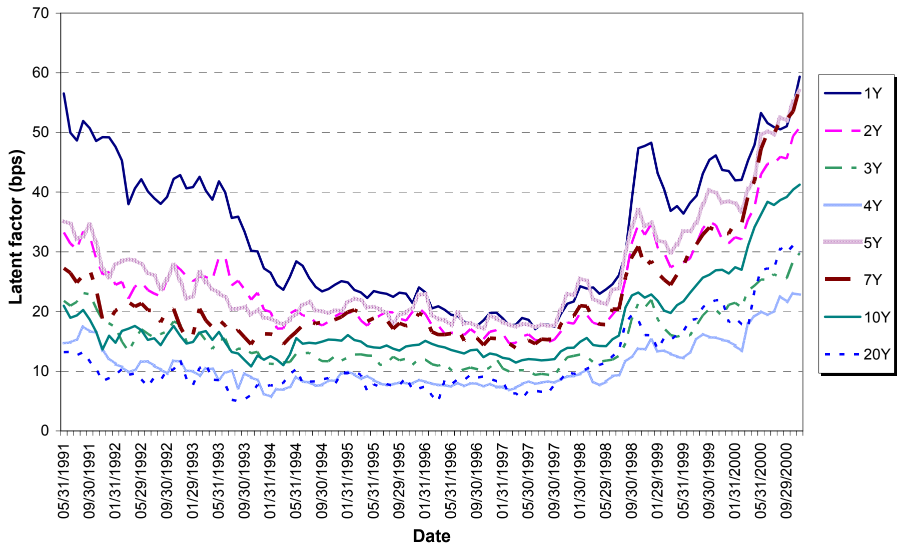

Figure 3: Maturity-based common latent factors in credit spreads

other maturity-based systematic credit spread components. Finally, whatever the sensitivity analysis level, namely sector, credit rating or maturity, corresponding common latent factors (i.e., systematic credit spread components as functions of sector, credit rating and maturity) exhibit a U-shaped behavior over our time horizon. We notice a monotonous increase of their respective levels from mid-1997 to the end of our time horizon (November 2000, which coincides with the end of the business cycle growth trend). Recall that we faced many economic events and financial facts during this time period. Indeed, we faced the Asian crisis in 1997, the Russian default as well as LTCM hedge fund collapse in 1998, the shortage of US Treasury bonds due to massive buybacks as well as the beginning of flight-to-quality phenomenon on bonds in 1999/2000, and finally the multimedia bubble burst in 2000.[12] Such events support the widening of credit spreads due to a deterioration of both systematic risk and/or default risk (and therefore a degradation of credit risk).

In unreported results, we computed also the unsystematic credit spread components corresponding to related sector-, credit rating- and maturity-based systematic components in US corporate credit spreads. The percentage of unsystematic risk components in credit spreads at sector, rating and maturity levels lies on average between 29.0041, 15.4545, 16.0915 and 78.4485, 72.7654, 71.2222 percent respectively. To get a view, we plot in figures 4 to 6 corresponding median values as well as related standard deviations.

At a sector risk level (see figure 4), the median value of the unsystematic credit spread component decreases when rating quality increases, and it also increases with maturity. Moreover, median values of unsystematic sector-specific credit spread components are generally the highest for IN sector. At a rating risk level (see figure 5), the median value of the unsystematic credit spread component increases with maturity. At a maturity risk level (see figure 6), the median value of the unsystematic credit spread component increases with both rating quality and maturity. The sector-, rating- and maturity-based unsystematic components in credit spreads have some significance insofar as they capture the default components (i.e., issuer-specific risk) as well as liquidity shocks on (i.e., bond-specific risk of) US corporate credit spreads. Such components are not encompassed in systematic factors.

[12] From November 1999 to April 2000, internet unlocked share values became around four times higher (see Ofek & Richardson (2003)).

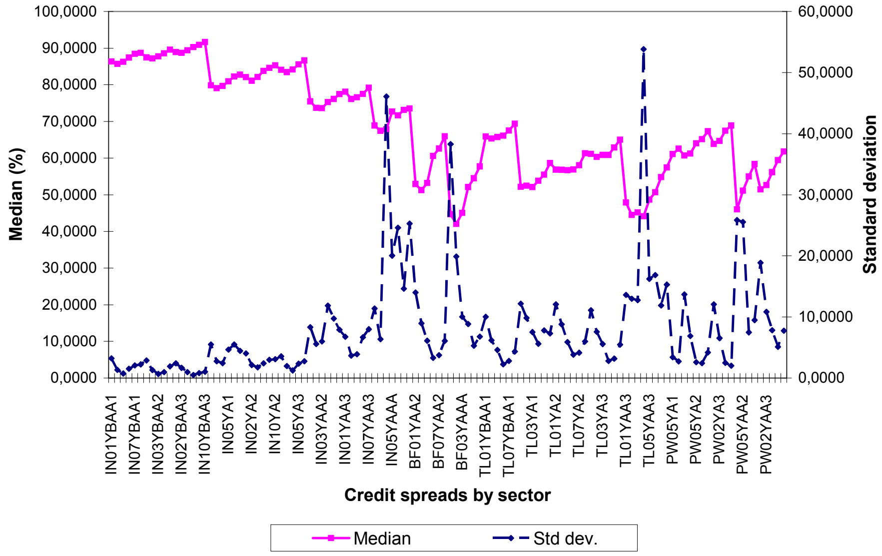

Figure 4: Unsystematic sector-specific components in credit spreads

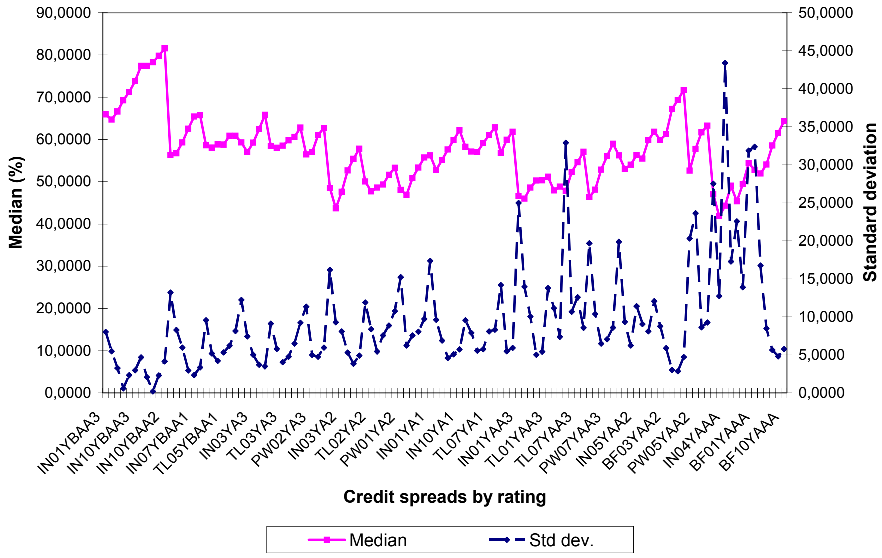

Figure 5: Unsystematic rating-based components in credit spreads

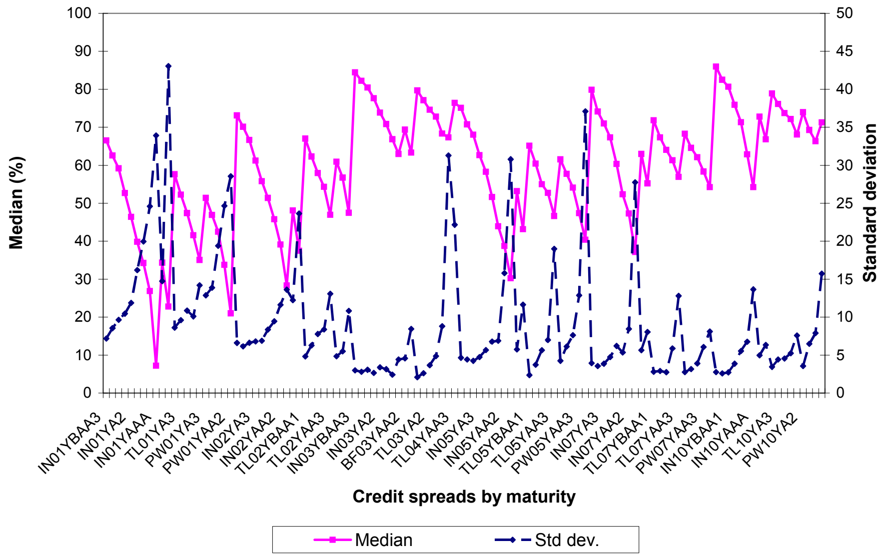

Figure 6: Unsystematic maturity-based components in credit spreads

Moreover, Sun, Lin & Nieh (2005) underline the significant information content of idiosyncratic credit spread components. Indeed, idiosyncratic credit spread components are shown to exhibit a high predictive power for future default rates whereas full/global credit spreads do not.

Finally, to set the global credit risk frame, we introduce a new absolute risk measure σ^* to avoid biases due to the asymmetric properties of our data time series. Specifically, σ^* is the average absolute distance between a given time series and its corresponding median value. We label $\sigma^*(M_t)$ the absolute risk measure of our sector-specific, rating-based and maturity-based systematic factors in credit spreads, and $\sigma^*(CS_t)$ the absolute risk measure of our corporate credit spreads. Namely, we state:

$$\sigma^*(M_t) = \frac{1}{T}\sum_{t=1}^{T} |M_t - Median(M_t)| \tag{3}$$

$$\sigma^*(CS_t) = \frac{1}{T}\sum_{t=1}^{T} |CS_t - Median(CS_t)| \tag{4}$$

Table 18: Average absolute sector risk measure in basis points

	IN	BF	TL	PW
$\sigma^*(M_t)$	3.6573	6.2651	6.7748	5.6385

Table 19: Average absolute rating-based risk measure in basis points

	BAA3	BAA2	BAA1	A3	A2	A1	AA3	AA2	AAA
$\sigma^*(M_t)$	11.9434	6.6287	8.3943	6.7812	7.7393	5.9280	6.2911	4.8408	5.0737

Hence, $\sigma^*(CS_t)$ represents some average global credit risk distance (as compared to some median credit spread value) whereas $\sigma^*(M_t)$ represents some average systematic credit risk distance.[13] Arguably, such a specification helps account for credit spread distribution as well as impact of related high/extreme values.[14] Corresponding absolute risk values are given in tables 18 to 20 for systematic credit risk factors as functions of sector, rating and maturity.[15]

At sector, rating and maturity levels, the average systematic absolute risk measure is the lowest for IN sector, AA2 rating grade, and four-year maturity respectively. In the same way, the average systematic absolute risk measure is the highest for TL sector, BAA3 rating grade, and one-year maturity. To get a global view, we also compute the proportion of systematic credit risk in the global credit risk level as $p = \frac{\sigma^*(M_t)}{\sigma^*(CS_t)} \times 100$. Hence, p represents a systematic credit risk measure (as compared to some global credit risk level). Related average values are also given in table 21 for each sensitivity analysis level, namely sector, rating and maturity.[16]

[13] Recall that our data are expressed in basis points.

[14] Analogously, we introduce in the appendix other median-related/modified descriptive statistics such as modified standard deviation, skewness and kurtosis.

[15] To spare space, we do not provide credit spread-related results, which require to display three times 116 values (i.e., for sector, rating and maturity analysis levels).

[16] At each sensitivity analysis level (i.e., sector, rating and maturity), we compute first proportion p for each available credit spread data, and we compute then the related arith-

Table 20: Average absolute maturity-based risk measure in basis points

	1Y	2Y	3Y	4Y	5Y	7Y	10Y	20Y
$\sigma^*(M_t)$	10.7651	6.4240	3.7684	2.9124	6.8559	5.9461	4.4192	4.0739

Table 21: Average systematic risk by sector, rating and maturity in percent

	Sector	Rating	Maturity
p	30.2765	37.4996	38.1275

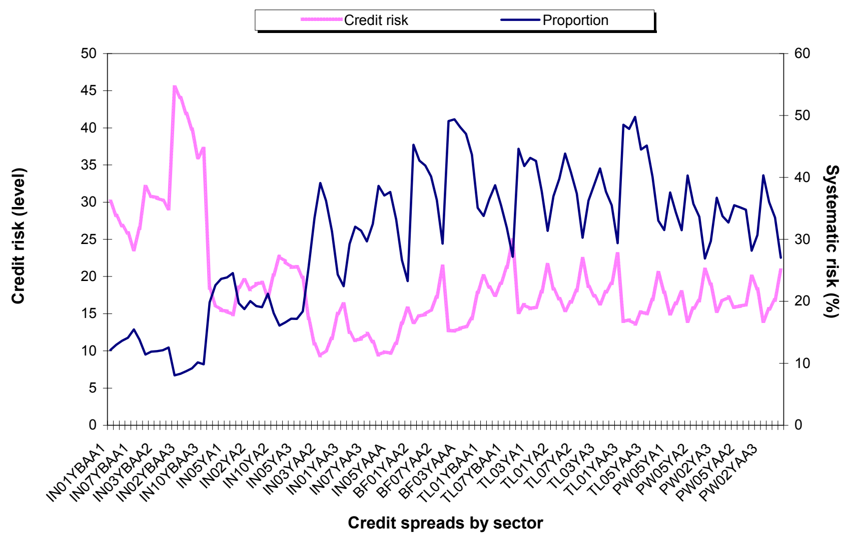

Figure 7: Sector-specific credit risk and systematic credit risk

On an average basis, systematic credit risk is the highest at a maturity sensitivity analysis level. Moreover, we also plot both proportion p for all considered credit spreads as well as corresponding credit risk distances for each sector, rating and maturity analysis level (see figures 7 to 9).

Plots illustrate obviously the results that are summarized in previous tables. As a conclusion, our results support the findings of Koopman, Lucas & Monteiro (2005) who advocate a dynamic common latent component in explaining credit rating migrations. They understand this common component as a credit cycle and exhibit its asymmetric impact on credit rating downgrade and upgrade probabilities. Indeed, we easily notice the differences in rating-based systematic components in credit spreads. Furthermore, our results emphasize systematic credit risk portfolio management in the light of sector, rating and maturity risk profiles (see Wilson (1997a,b)). As a rough

metic mean across all credit spreads.

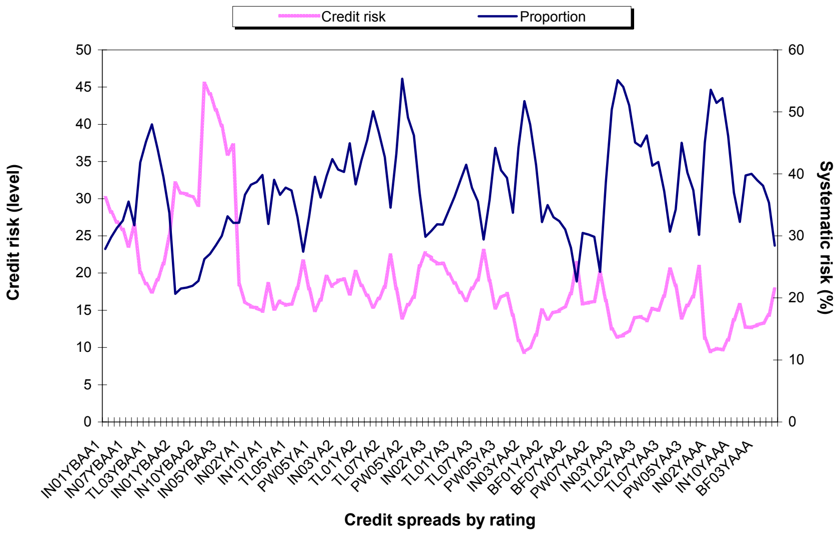

Figure 8: Rating-based credit risk and systematic credit risk

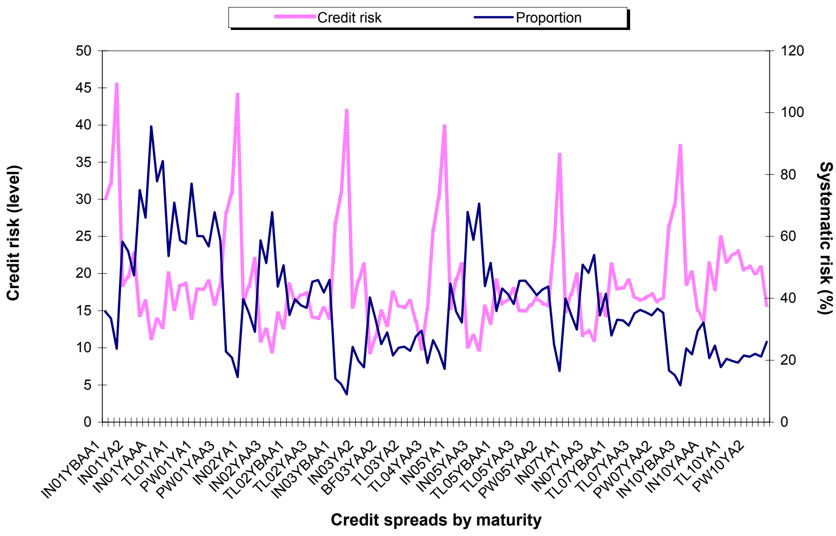

Figure 9: Maturity-based credit risk and systematic credit risk

guide, we also iterated the Kalman estimation procedure to extract the remaining common unobserved component in estimated latent factors for each risk level analysis. Inconclusive corresponding results are briefly summarized in the appendix.

4 Latent factor versus S&P 500 index

This section attempts to capture and describe soundly the risk structure prevailing between US credit spreads and the US financial market when this one is assumed to be described by S&P 500 stock index. Namely, we address two specific questions. Is the S&P 500 index a good representative (in a statistical sense) of the common latent factor in credit spreads as a function of industry, credit rating and maturity? What is the link prevailing between the common latent factor in US credit spreads and S&P 500 index in the light of the three previous risk levels? Such issues are important for credit risk assessment and credit risk forecast prospects. Indeed, managing dynamically the systematic component in credit spreads requires quantifying soundly such a risk component.

4.1 Methodology

Flexible least squares (FLS) principle is a robust non-linear estimation method, which can handle data correlation schemes and stochastic parameters generated by non-stationary processes (see Kalaba & Tesfatsion (1988, 1989, 1990) and Kladroba (2005)). We employ FLS methodology to run regressions of sector-specific, rating-based and maturity-based systematic factors M_t in credit spreads (i.e., common latent factors in credit spreads as functions of industry, rating and maturity) on S&P 500 index returns R_t. Recall that we consider credit spreads in basis points, and therefore express S&P 500 index returns in basis points for data homogeneity purpose. Consider the following regression equation for each available sector, credit rating and maturity risk level:

$$M_t = a_t + b_t \times R_t + u_t \tag{5}$$

where a_t and b_t are FLS time-varying regression coefficients, and (u_t) are residual measurement errors related to each time step t in $\{1, \cdots, T\}$. Specifically, a_t is also expressed in basis points and represents that part of systematic credit spread component that is unexplained by S&P 500 index.[17] Moreover, b_t illustrates market influence (i.e., impact of S&P 500 index) on the systematic credit risk component M_t over time. Finally, residual error u_t may catch state-specific tax effects, market-specific liquidity effects, and market anomalies such as announcement effects among others. Regression equation (5) can be rewritten simply as:

$$M_t = X_t \cdot B_t + u_t$$

where $X_t = \left[\begin{array}{cc} 1 & R_t \end{array}\right]$ and $B_t = \left[\begin{array}{c} a_t \\ b_t \end{array}\right]$ for each time t. Under FLS setting, former measurement errors (see equation 6) and dynamic specification errors (see equation 7) are assumed to be approximately zero.

$$M_t - X_t \cdot B_t = u_t \approx 0 \tag{6}$$

$$B_t - B_{t-1} \approx 0 \tag{7}$$

Indeed, consider now related sum of squared residual measurement errors $E_M^2(B)$ and sum of squared dynamic specification errors $E_D^2(B)$ as follows:

$$E_M^2(B) = \sum_{t=1}^{T} (M_t - X_t \cdot B_t)^2 = \sum_{t=1}^{T} u_t^2 \tag{8}$$

$$E_D^2(B) = \sum_{t=1}^{T} (B_t - B_{t-1})^T \cdot (B_t - B_{t-1}) \tag{9}$$

where A^T is the transposition of matrix A and $B = (B_t)_{1 \leq t \leq T}$. Each of the previous sums (8) and (9) represents an estimation cost. Specifically, FLS methodology focuses on the objective function $OF(B)$ as follows:

$$OF(B) = \sum_{t=1}^{T} (M_t - X_t \cdot B_t)^2 + \sum_{t=1}^{T} (B_t - B_{t-1})^T \cdot MU \cdot (B_t - B_{t-1}) \tag{10}$$

where $MU = \left[\begin{array}{cc} \mu_1 & 0 \\ 0 & \mu_2 \end{array}\right]$ is the incompatibility cost matrix. Hence, the objective function considers the sum of squared residual measurement error

[17] In fact, a_t is the systematic credit spread component's trend over time, this component being independent of market index S&P 500.

and squared dynamic specification error sums, the sum of squared dynamic specification errors being weighted by a given cost matrix with positive coefficients. In particular, the sum of squared residual measurement errors accounts for equation errors whereas the sum of squared dynamic specification errors accounts for FLS coefficient variation. For a specified incompatibility cost matrix and conditional on a given set of observations $(M_t, R_t)_{1\leq t\leq T}$, FLS methodology investigates minimal pairs of squared residual measurement error and squared dynamic error sums. Such minimal pairs result from the optimal coefficient sequences $\hat{B}^{FLS} = \left(\hat{B}_t^{FLS}\right)_{1\leq t\leq T}$ that are sought. A small incompatibility cost coefficient lowers the impact of coefficient variation in the objective function. Therefore, FLS coefficients exhibit more volatile time-paths. Conversely, a large incompatibility cost coefficient increases substantially the impact of coefficient variation in the objective function. Consequently, FLS coefficient estimates exhibit smooth or even almost constant time-paths. Finally, the optimal FLS coefficient estimates target the minimization of the objective function such that:

$$\begin{aligned}\hat{B}^{FLS} &= Arg\min OF\left(B\right) \\ &= \min_{B}\left\{\sum_{t=1}^{T}\left(M_t - X_t\cdot B_t\right)^2 + \sum_{t=1}^{T}\left(B_t - B_{t-1}\right)^T\cdot MU\cdot\left(B_t - B_{t-1}\right)\right\}\end{aligned} \tag{11}$$

Hence, $\hat{B}^{FLS}$ is inferred so that previous sums of squared errors $E_M^2\left(B\right)$ and $E_D^2\left(B\right)$ are as small as possible to satisfy equations (6) and (7) given observed $(M_t, R_t)_{1\leq t\leq T}$ time series.

Running FLS regressions of sector-, rating- and maturity-based systematic factors in US corporate credit spreads on S&P 500 index returns allows then for investigating to what extent S&P 500 index helps identify the systematic risk level in risky bonds (i.e., in credit portfolios). We will infer related FLS estimates and exhibit the proportion of systematic latent factors, which is explained by S&P 500 index in the light credit spreads' sectors, ratings and maturities. Related FLS coefficient estimates leading then to an instructive three-level analysis setting.

Table 22: Incompatibility cost parameters for common latent factors

	Sector	Rating	Maturity
μ_1	0.1	0.001	0.1
μ_2	0.1	0.001	0.1

Table 23: Statistics for FLS estimates of systematic sector-specific factors

	Statistics	IN	BF	TL	PW
a_t	Median	8.4370	19.2470	23.4505	19.2598
	Standard deviation	0.7999	0.8894	0.5631	0.3268
	Skewness	0.9289	0.8159	-0.1402	-0.0610
	Excess kurtosis	-0.5495	-0.1910	-1.1421	-1.3610
b_t	Median	-0.0018	-0.0033	-0.0069	-0.0044
	Standard deviation	0.1287	0.2148	0.1831	0.1412
	Skewness	3.5374	3.7399	1.2984	-1.3652
	Excess kurtosis	31.2062	36.5693	17.3747	14.7543

4.2 Econometric results

We run our FLS regressions and infer corresponding time-varying regression coefficient estimates (a_t, b_t). Under such a setting, table 22 displays related cost parameters for each systematic sector-specific, rating-based and maturity-based factor in credit spreads. These parameters are the lowest for rating-based systematic factors (i.e., rating-based FLS regression estimates are more volatile). For each risk dimension (i.e., sector-specific, rating-based or maturity-based analysis level) , the optimal cost parameters are the same for all systematic factors under consideration. Then, tables 23 to 25 exhibit some relevant descriptive statistics about corresponding FLS coefficient estimates.

At a sector level, the median value of a_t coefficient is the highest for TL sector systematic component and the lowest for IN sector systematic component. The set of a_t coefficients exhibits a negative excess kurtosis. Moreover, a_t time series of IN and BF sector systematic components are right-skewed whereas the ones of TL and PW sector systematic components are left-skewed. With regard to b_t time series, they exhibit negative median values and positive excess kurtosis whatever the sector. Specifically, b_t time series of IN, BF and TL sector systematic components are right-skewed

Table 24: Statistics for FLS estimates of systematic rating-based factors

Rating	a_t Median	a_t Std. dev.	a_t Skewness	a_t Excess kurtosis	b_t Median	b_t Std. dev.	b_t Skewness	b_t Excess kurtosis
AAA	17.7565	1.6492	0.9239	0.2839	-0.0054	0.1196	-0.3599	11.4727
AA2	16.6037	1.8218	0.7432	-0.0963	-0.0025	0.1066	0.4111	12.2355
AA3	20.7394	1.7049	0.5515	-1.1554	-0.0025	0.1355	-1.1475	11.6329
A1	20.9492	1.8840	0.7286	-0.2426	-0.0043	0.1240	-0.9679	10.4358
A2	27.5172	2.6982	0.6739	-0.4742	-0.0025	0.1513	-1.5553	10.8029
A3	24.8401	2.3891	0.7735	-0.3968	-0.0053	0.1261	-1.6413	9.7440
BAA2	29.1274	3.1716	0.8663	-0.0906	-0.0074	0.1664	-0.8830	10.6656
BAA2	16.6487	3.9541	0.8912	-0.5591	-0.0048	0.1112	-1.3057	10.4172
BAA3	29.9979	6.6330	0.8208	-0.3735	-0.0087	0.2043	-0.5602	14.4873

whereas the one of PW sector systematic component is left-skewed.

At a rating level, the median value of a_t coefficient is the highest for BAA3 rating-based systematic component and the lowest for AA2 rating-based systematic component. The set of a_t coefficients is right-skewed for all rating grades. Moreover, a_t time series of all rating-based systematic components exhibit a negative excess kurtosis except for AAA rating-based systematic component whose excess kurtosis is positive. With regard to b_t time series, they exhibit negative median values and positive excess kurtosis whatever the rating grade. Specifically, b_t time series of all rating-based systematic components are left-skewed except for AA2 rating-based systematic component whose b_t time series is right-skewed.

At a maturity level, the median value of a_t coefficient is the highest for four-year maturity-based systematic component and the lowest for one-year maturity-based systematic component. The set of a_t coefficients is right-skewed and exhibits a negative excess kurtosis for all maturities. With regard to b_t time series, they exhibit negative median values and positive excess kurtosis whatever the maturity. Specifically, b_t time series of all maturity-based systematic components are left-skewed except for four-year and twenty-year maturity-based systematic components whose b_t time series are right-skewed.

To get a view, we also plot the FLS regression estimates we get for the

Table 25: Statistics for FLS estimates of systematic maturity-based factors

Maturity	a_t				b_t			
	Median	Std. dev.	Skewness	Excess kurtosis	Median	Std. dev.	Skewness	Excess kurtosis
1Y	28.1700	6.2287	0.8999	-0.4326	-0.0075	0.1786	-0.6606	13.5091
2Y	21.8248	2.5293	0.7267	-0.4711	-0.0041	0.1248	-1.2043	9.9850
3Y	13.3776	1.7981	0.9639	-0.0444	-0.0009	0.0796	-0.3901	15.6875
4Y	9.6441	1.1081	0.6930	-0.1316	-0.0017	0.0622	0.3630	12.2210
5Y	24.6319	2.0632	0.7949	-0.1708	-0.0071	0.1424	-0.4589	8.6655
7Y	20.1919	1.4744	0.5701	-1.2015	-0.0039	0.1243	-0.7097	9.7946
10Y	15.6335	0.9561	0.6013	-1.2019	-0.0027	0.0886	-2.0296	14.1420
20Y	9.9893	2.1206	0.3964	-1.2656	-0.0015	0.0675	0.2890	8.0380

systematic latent factors in credit spreads as functions of their respective sector, rating and maturity (see figures 10 to 15). For clearness reasons, some complementary bidimensional graphs are displayed in the appendix. This way, we can observe the respective evolutions of FLS regression estimates over time as functions of credit spreads' sectors, ratings and maturities.

With regard to a_t coefficient estimates, corresponding plots illustrate the previous results exhibited by related descriptive statistics. Notice that a_t estimate times series for all sector-specific, rating-based and maturity-based latent factors generally decreases until 1996 and starts increasing from 1997 until November 2000 (i.e., end of our time horizon).

With regard to b_t coefficient estimates, b_t coefficient estimates exhibit generally the same evolution over time (i.e., common trend) whatever the considered systematic latent component in US corporate credit spreads. Moreover, their evolutions over time are far more irregular (i.e., jump-shaped around zero threshold) than the ones of corresponding a_t coefficient estimates whatever the considered systematic latent factor in credit spreads (i.e., sector-specific, rating-based or maturity-based). Indeed, they frequently jump from negative values to positive values, and conversely. Hence, sector-specific, rating-based or maturity-based systematic components in credit spreads frequently move in the same direction as, and conversely in the opposite direction as S&P 500 index return. By the way, b_t coefficient estimates never take

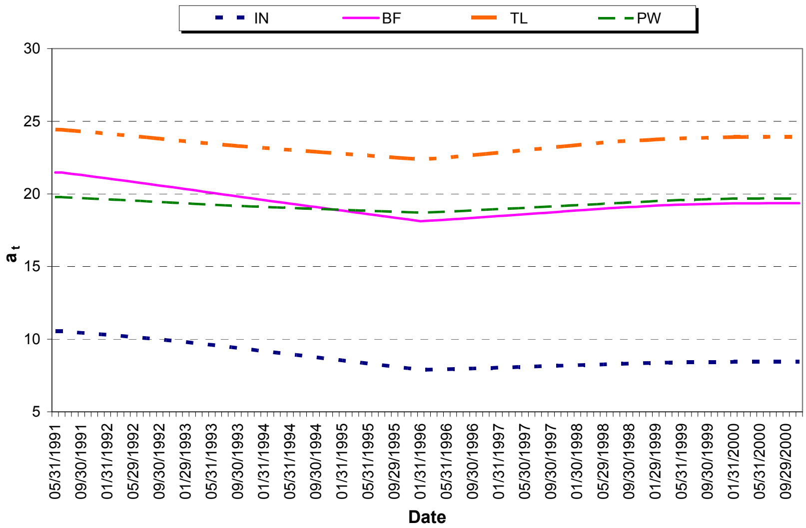

Figure 10: FLS estimates for sector-specific systematic factors

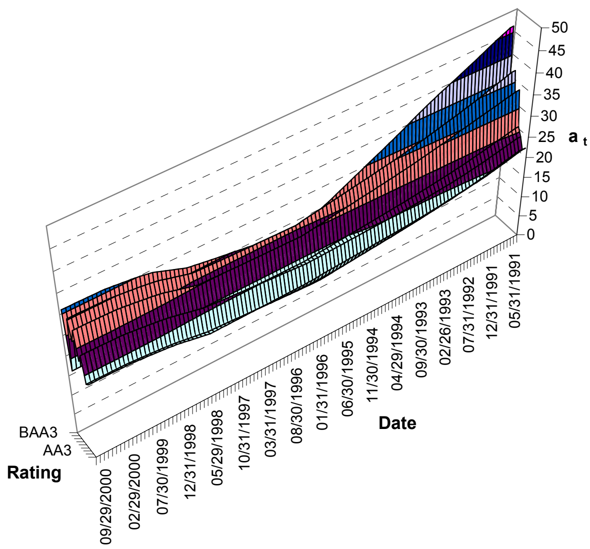

Figure 11: FLS estimates for rating-based systematic factors

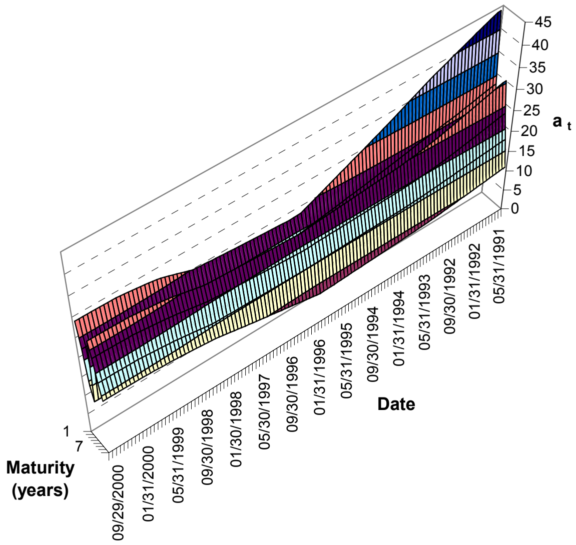

Figure 12: FLS estimates for maturity-based systematic factors

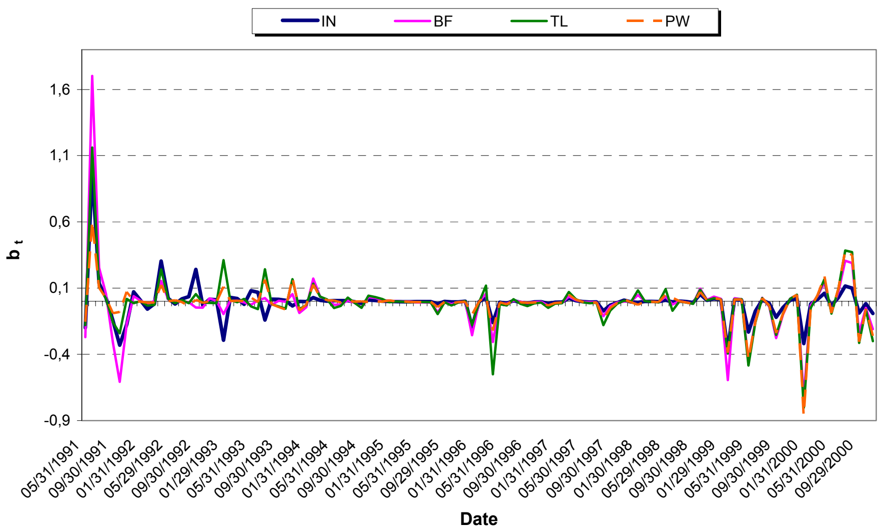

Figure 13: FLS coefficient estimates for sector-specific systematic factors

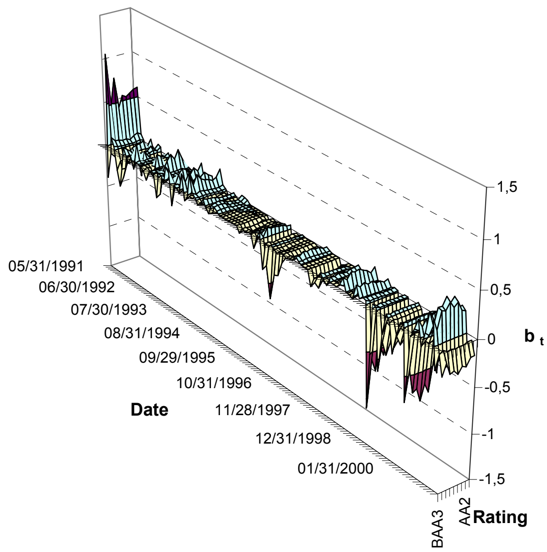

Figure 14: FLS coefficient estimates for rating-based systematic factors

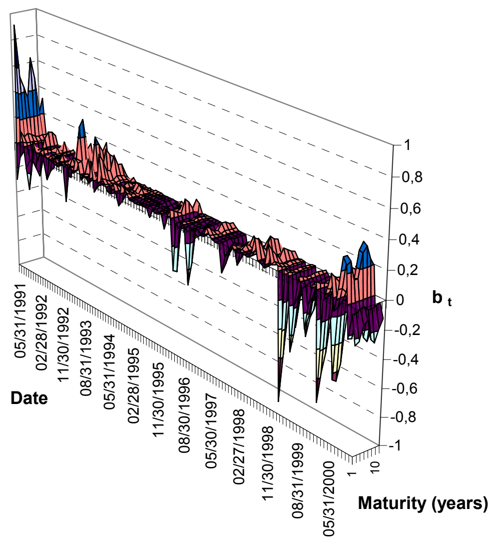

Figure 15: FLS coefficient estimates for maturity-based systematic factors

the unit value[18] whatever the considered systematic sector-specific, rating-based and maturity-based systematic components. Such a feature has a high significance insofar as b_t coefficient estimates should be unity/constant if S&P 500 market index were a perfect/good proxy of the systematic component (i.e., common latent component) in credit spreads as a function of sector, rating and maturity. Therefore, S&P 500 index is a biased proxy of the systematic risk component in US corporate credit spreads as a function of industry, rating and maturity. In unreported results, we computed the non-parametric correlation coefficients (i.e., Spearman's rho and Kendall's tau) between S&P 500 index return and both credit spreads and related systematic sector-specific, rating-based and maturity-based components. We find that these correlation coefficients lie between -0.3000 and 0, and are all insignificant at a five percent bilateral test level. Then, such results support the findings of Campbell *et al.* (2001) who showed that the idiosyncratic risk component in S&P 500 index has skyrocketed during the 90'. Consequently, S&P 500 index is not diversified enough to represent appropriately the US financial market (i.e., market risk) at least over our studied time horizon. Such an issue makes it difficult to capture the systematic component in credit spreads as a function of sector, rating and maturity while employing S&P 500 index as a market proxy. This puzzle is of high significance insofar as the chosen market proxy impacts the accuracy and quality of risk quantification when distinguishing between the systematic part (i.e., market influence) and the idiosyncratic (i.e., unsystematic) part of credit risk (e.g., bidimensional Value-at-Risk quantification tool).

To bypass such a puzzle, credit risk managers should focus on the dynamic link prevailing between S&P 500 index and US corporate credit spreads in the light of their respective industries, ratings and maturities. This way, they could extract the systematic component in credit risk, and integrate this market component into credit risk valuation processes. To get a view of such a link, we focus on the proportions of sector-specific, rating-based and maturity-based systematic components in credit spreads (i.e., common latent factors in credit spreads as functions of sector, rating and maturity), which are explained (i.e., $\frac{b_t R_t}{M_t} \times 100$) by S&P 500 index return (see tables 26 to 28).[19] The proportions of explained sector-specific, rating-based and

[18] In unreported results, we clearly notice that b_t time series only crosses up or down the unit threshold value.

[19] Notice that the standard deviation of explained systematic sector-specific, rating-

Table 26: Proportions of explained systematic sector-based factors in percent

	IN	BF	TL	PW
Median	27.1192	16.7924	20.4539	14.6739
Standard deviation	15.5532	16.3837	14.4102	16.8517
Skewness	-0.0142	0.6289	0.7354	0.9501
Excess kurtosis	-1.1518	-0.7374	0.1790	0.1098

Table 27: Proportions of explained systematic rating-based factors in percent

Rating	Median	Standard deviation	Skewness	Excess kurtosis
AAA	20.5449	14.3622	0.5381	-0.4190
AA2	11.8669	14.1185	1.0748	0.4434
AA3	14.2405	14.7331	0.8781	0.1749
A1	13.8904	14.3840	0.9331	0.2105
A2	11.1569	14.5083	1.0018	0.1890
A3	14.2416	13.5309	0.7464	-0.1613
BAA1	16.4819	13.4592	0.4387	-0.7303
BAA2	19.3530	14.0011	0.3778	-0.8968
BAA3	16.7319	13.0014	0.4401	-0.8167

maturity-based systematic components in credit spreads are reported in absolute value.

At a sector level, the corresponding median proportion value is the lowest for PW sector and the highest for IN sector. All proportion time series are right-skewed except for the proportion of IN sector systematic component, which is explained by S&P 500 index return. Moreover, these proportion times series exhibit a negative excess kurtosis for IN and BF sectors whereas they exhibit a positive excess kurtosis for the proportions of explained TL and PW sector systematic components. At a rating level, the corresponding median proportion value is the lowest for A2 rating grade and the highest for AAA rating grade. All these proportion time series are right-skewed. Moreover, only the proportions of explained AA2, AA3, A1 and A2 rating-based systematic components exhibit a negative excess kurtosis, the other rating-

based and maturity-based components in credit spreads represents the sensitivity of credit risk (as proxied by credit spreads' volatility) to market risk (as proxied by the standard deviation of explained systematic credit spread factors) as a function of industry, rating and maturity.

Table 28: Proportions of explained systematic maturity-based factors in percent

Maturity	Median	Standard deviation	Skewness	Excess kurtosis
1Y	16.4129	13.4630	0.4299	-0.8775
2Y	15.3528	13.7857	0.8517	0.0920
3Y	13.7789	13.7416	0.9146	-0.0031
4Y	12.0573	15.1499	1.1787	0.7595
5Y	19.3014	12.6136	0.4395	-0.2257
7Y	17.1784	14.4299	0.8495	0.2837
10Y	13.4585	14.9908	0.9267	0.1098
20Y	15.2368	19.4691	1.2188	0.7787

based proportions exhibiting a positive excess kurtosis. At a maturity level, the corresponding median proportion value is the lowest for the four-year maturity and the highest for the five-year maturity. All these proportion time series are right-skewed. Moreover, these proportion times series exhibit generally a positive excess kurtosis except for the proportions of explained one-year, three-year and five-year maturity-based systematic components (i.e., negative excess kurtosis).

We also plot related FLS graphs to visualize the evolution over time of the proportions of sector-specific, rating-based and maturity-based systematic components in credit spreads, which are explained by S&P 500 index return (see figures 16 to 18).

Whatever the considered risk level analysis, S&P 500 index fails obviously to capture the systematic sector-specific, rating-based and maturity-based components in corporate credit spreads. Moreover, related time series are highly fluctuating over our time horizon. Consequently, the sensitivity of US corporate credit spreads to S&P 500 index is strongly fluctuating over time and often low (see table 29 below). Moreover, the maximum proportions of systematic credit spread components that are explained by S&P 500 index consist respectively of 63.6223%, 58.5844% and 86.3508% / 59.8807% at sector, rating and twenty-year / other-year maturity levels. Namely, the explanatory power/performance of S&P 500 index with regard to sector-specific, rating-based and maturity-based systematic credit spread components is generally poor and specifically low (i.e., pronounced weak values) for 1992/mid-1993, mid-1994/1995 and mid-1997/September 1998 time periods.

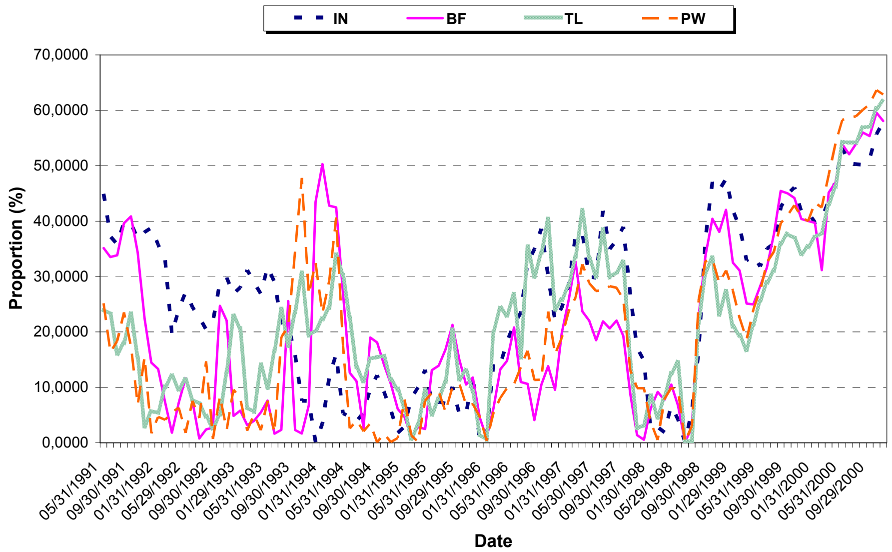

Figure 16: Proportions of explained systematic sector-based factors

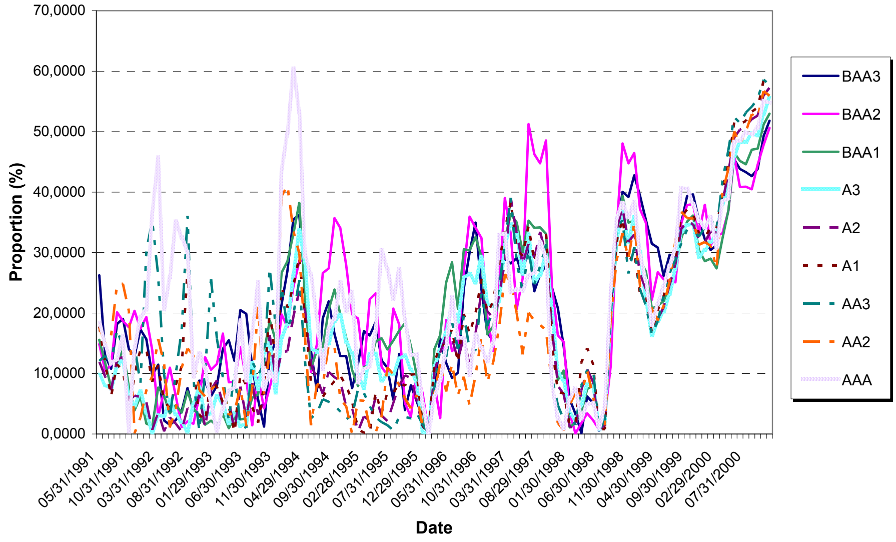

Figure 17: Proportions of explained systematic rating-based factors

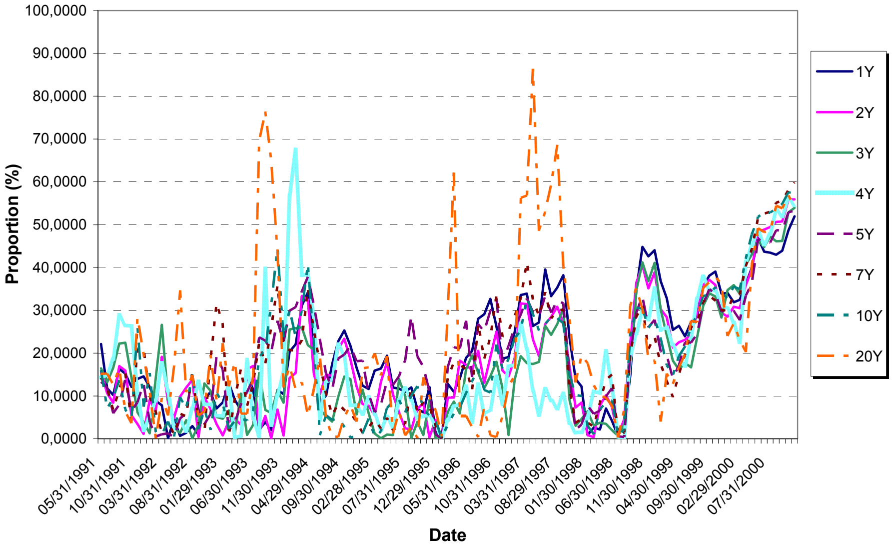

Figure 18: Proportions of explained systematic maturity-based factors

Table 29: Proportions of credit spreads explained by SP500 index in percent

Statistics*	Sector	Rating	Maturity
Mean	7.1893	7.7041	7.8816
Median	6.2649	6.5454	6.3001
Minimum	0.0269	0.0124	0.0127
Maximum	43.7707	46.8931	51.3896

*Average values across sector-specific, rating-based and maturity-based credit spreads.

5 Conclusion

Starting from the well-documented dependency between credit risk and market risk, we investigated the prevailing relationship between US corporate credit spreads and S&P 500 stock index. Focusing on the bivariate risk profile of credit spreads (i.e., the bivariate structure of credit risk, namely market and default risk components), we analyzed the interaction and impact of related systematic/market and idiosyncratic/unsystematic/default risk components on credit risk level in the light of three dimensions. The corresponding dimensions are industry-, credit rating- and maturity-based sensitivity analyses. Specifically, we investigated the systematic and idiosyncratic credit risk components implied by US corporate credit spreads. Our aggregate credit rating levels allowed for comparison across credit rating grades while investigating the common hidden information content in credit spreads as a function of credit ratings. Furthermore, we achieved a two-stage study focusing on both the sensitivity of credit spreads to globally unobserved macro/systematic factors (i.e., sensitivity of credit risk to business cycle, or equivalently macroeconomic/systematic shocks) and both the coherency and usefulness of S&P 500 stock index as a proxy of systematic risk factor for such credit spreads. This two-stage study was run in the light of respective credit spreads' sectors, ratings and maturities.

First, we extracted the common unobserved component of default risk (i.e., common latent factor) from observed credit spread data in the light of three risk dimensions, namely industry, credit rating and maturity. This component represents the interaction between credit risk and market risk (i.e., the systematic component of credit risk). Indeed, credit risk is known to have two components, namely a market/systematic risk component and an unsystematic/default risk component. The latter component may incorporate liquidity effects that are peculiar to debt security or eventually to the traded asset class. We showed that credit risk sensitivity to market risk depends on the level of the study that is achieved. Specifically, we analyzed credit spreads' sensitivity to the financial market or to the business cycle according to three levels: economic sector, credit rating, and finally maturity. Indeed, we found that the sensitivity of US corporate credit spreads to market risk (i.e., systematic credit spread components) depends on the industry, rating and maturity under consideration. Incidentally, related systematic credit spread components exhibit a U-shaped evolution over our time horizon whatever the sensitivity analysis level (i.e., we lie essentially on a growth business cycle trend). By the way, the previous three risk dimensions play a significant role for credit portfolio and credit line managers (see Wilson (1997a,b)), depending on the management style that is applied (e.g., time diversification, sector diversification, asset concentration). Most importantly, the common latent factor captures credit risk correlation, which is important for valuing multiname credit derivatives for example.

Second, we attempted to assess the link prevailing between US credit spreads and related S&P 500 index, which is commonly thought as a proxy of the systematic/market risk factor (i.e., market portfolio). We found negative and insignificant non-parametric correlation coefficients (i.e., Spearman's rho and Kendall's tau) between common latent factors (i.e., systematic credit spread components) and S&P 500 stock index return in the light of our basic three risk dimensions. Moreover, FLS regressions of systematic sector-specific, rating-based and maturity-based credit spread components on S&P 500 index returns emphasized that S&P 500 stock index is not a convenient proxy of the systematic component in credit spreads (i.e., common unobserved component). Indeed, the average proportion of systematic sector-specific, rating-based and maturity-based credit spread components that is explained by S&P 500 index return lies generally below forty three percent, this average proportion falling below eight percent for that part of sector-specific, rating-based and maturity-based credit spreads explained by S&P 500 index. Consequently, S&P 500 index fails to capture the systematic risk factor driving corporate credit spreads in the light of their respective sectors, ratings and maturities. However, FLS methodology exhibited the dynamic link prevailing between S&P 500 index return and systematic sector-specific, rating-based and maturity-based credit spread components over time. Therefore, estimating and anticipating soundly market influence on credit risk evolution requires filtering the information content of S&P 500 index return.

Of course, our sensitivity analysis has a significant added value since it yields important possible extensions and improvements for credit risk management. For predictability prospects, our decomposition can be employed first in a value-at-risk (VaR) credit risk assessment framework (i.e., bidimensional VaR for credit risk). Indeed, describing/forecasting credit spreads' (i.e., credit risk) evolution should require to describe/forecast jointly the related systematic/market component and unsystematic/default components (at sector, rating and maturity levels). Such a distinction should be employed in the VaR assessment process of credit risk insofar as the combination of market risk level with default risk levels determines corresponding observed credit risk levels (i.e., credit spreads) as functions of industry, credit rating and maturity. This bivariate framework allows for distinguishing whether widening/tightening of credit spreads results from market risk and/or default risk deterioration/improvement. Second, we employed Kalman linear methodology as a filtering tool. However, Kalman methodology could be employed as a forecasting tool in order to predict at least short term credit risk while forecasting systematic credit risk components as functions of sector, rating and maturity. Third, instead of considering credit spreads versus government yields, it could be instructive to study credit spreads versus corresponding swap rates in order to avoid bond-specific liquidity problems (see Liu, Longstaff & Mandell (2002) and Cooper, Hillman & Lynch (2001)). Finally, future research can undertake a three-dimension study while distinguishing between systematic, default-specific and liquidity-specific risk components in credit spreads always as functions of industry, credit rating and maturity. Such an issue will yield a more detailed and sensitive analysis of credit risk evolution in the light of our three previous risk levels (see Odders-White & Ready (2006)).

6 Appendix

We report in this section some useful estimates, results and graphs.

6.1 Kalman estimates

We display in tables below the most relevant and significant Kalman estimates we get while studying successively US corporate credit spreads at industry, credit rating and maturity risk levels (see tables 30 to 32). Recall that credit spreads are expressed in basis points and therefore M_0 (the initial value of the common latent component under consideration) is expressed in basis points.[20]

The systematic common unobserved components (i.e., systematic sector-specific components) peculiar to BF, TL , PW sectors exhibit a non-stable

[20] M_0 or M_t is that part of credit spreads, which results from systematic effects in those credit spreads in the light of their respective sector, rating and maturity.

Table 30: Kalman estimates for the sector analysis

	IN	BF	TL	PW
M_0	19.1372	32.8460	31.6207	25.7563
α_M	0.9987	1.0037	1.0137	1.0139
P_t	7.5495×10^{-15}	0.7170	0.3430	0.2670

Table 31: Kalman estimates for the rating analysis

Rating	M_0	α_M	P_t
AAA	27.0143	1.0065	0.7913
AA2	25.7708	1.0082	0.4863
AA3	26.9711	1.0145	0.6840
A1	30.6116	1.0106	0.6651
A2	37.8950	1.0110	0.9907
A3	33.4907	1.0097	0.7650
BAA1	43.5918	1.0067	0.9539
BAA2	31.1680	0.9985	0.1614
BAA3	62.0104	0.9981	0.7894

evolution over time (i.e., related α_M parameters are above unity) whereas the one peculiar to IN sector is stable over time.[21]

The systematic common unobserved components peculiar to all rating grades (i.e., systematic rating-based components) exhibit generally a non-stable evolution over time except for BAA3 and BAA2 rating grades.

The systematic common unobserved components peculiar to all maturities (i.e., systematic maturity-based components) exhibit generally a non-stable evolution over time except for the one-year maturity case.

6.2 Systematic components in credit spreads

We investigate briefly the proportion of systematic sector, rating- and maturity-based components in credit spreads. To get a view, we plot the

[21] Stability means that the common latent factor under consideration evolves and oscillates around some constant given level (whatever the magnitude of corresponding oscillations).

Table 32: Kalman estimates for the maturity analysis

Maturity	M_0	α_M	P_t
1Y	56.0358	0.9990	0.5471
2Y	32.7506	1.0075	0.4148
3Y	21.5347	1.0043	0.3991
4Y	14.6423	1.0058	0.2675
5Y	34.6564	1.0092	0.5817
7Y	26.6230	1.0170	0.3472
10Y	20.4114	1.0135	0.2105
20Y	13.0281	1.0124	0.2314

proportions of systematic components in US corporate credit spreads as functions of industry, credit rating and maturity (see figures 19 to 21).

At a sector level, median and mean values of the proportion of systematic sector-specific components in credit spreads are increasing functions of maturity and sectors. Namely, industrial credit spreads exhibit generally a lower proportion of systematic sector-specific component whereas power credit spreads exhibit usually a higher proportion of systematic sector-specific component.

At a rating level, median and mean values of the proportion of systematic rating-based components in credit spreads are generally increasing functions of maturity until two-year maturity and then become decreasing functions from two-year to ten/twenty-year maturities for IN, BF and PW sectors. This behavior does not apply to AAA industrial credit spreads as well as TL credit spreads whose evolutions are far more irregular.

At a maturity level, median and mean values of the proportion of systematic maturity-based components in credit spreads are decreasing functions of maturity. Namely, for given sector and maturity, median and mean values of the proportion of systematic maturity-based components in credit spreads are also increasing functions of credit rating grades.

6.3 Median-related descriptive statistics

We introduce modified standard deviation, skewness and kurtosis statistics that are based on a median specification. Indeed, we apply the classic

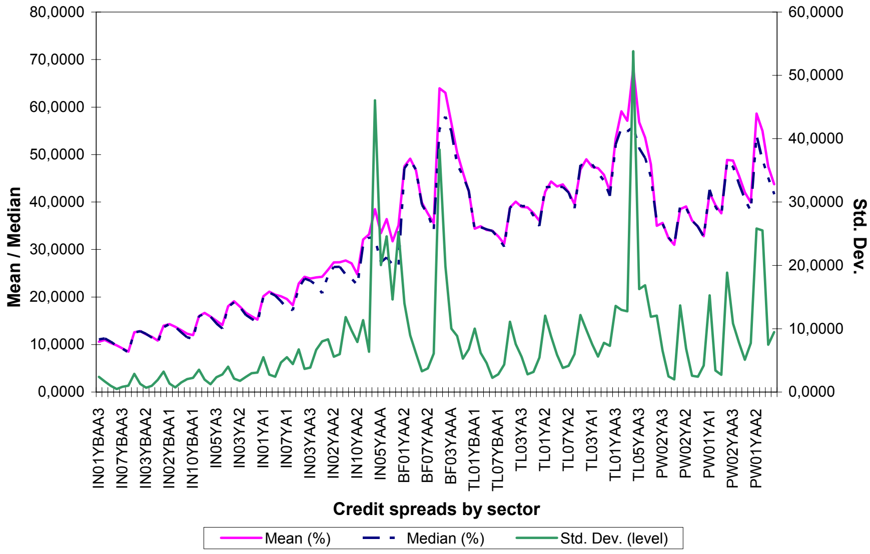

Figure 19: Proportion of systematic sector-specific components in credit spreads

descriptive statistics principle except that we modify slightly the classic statistics definition. Namely, we employ the time series median as a reference rather than its related arithmetic mean. Specifically, we consider the distance between a time series and its corresponding median value rather than its related mean. For this purpose, we introduce new modified standard deviation (σ_{Mod}), skewness ($Skewness_{Mod}$) and kurtosis ($Kurtosis_{Mod}$) as follows for any time series (X_t) with T observations:

$$\sigma_{Mod} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(X_t - Median\left(X_t\right)\right)^2} \tag{12}$$

$$Skewness_{Mod} = \frac{1}{\sigma_{Mod}^3} \times \frac{1}{T}\sum_{t=1}^{T}\left(X_t - Median\left(X_t\right)\right)^3 \tag{13}$$

$$Kurtosis_{Mod} = \frac{1}{\sigma_{Mod}^4} \times \frac{1}{T}\sum_{t=1}^{T}\left(X_t - Median\left(X_t\right)\right)^4 \tag{14}$$

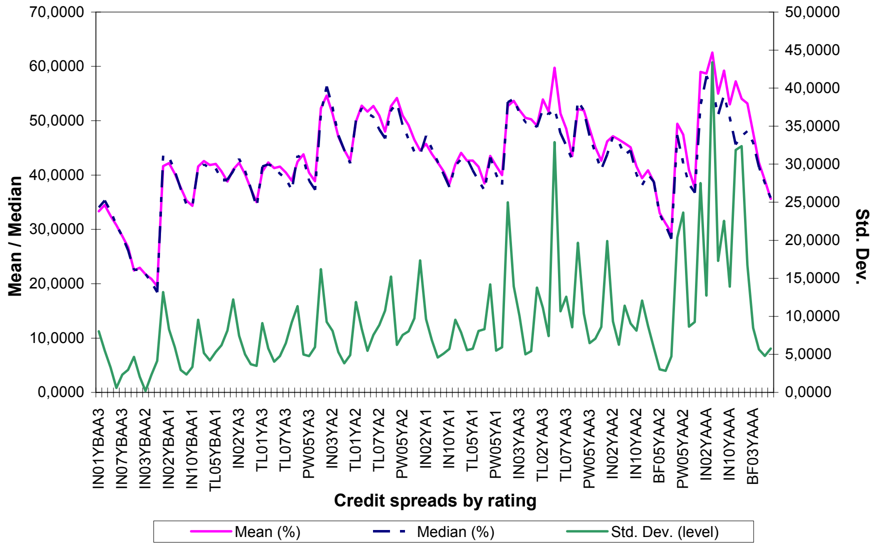

Figure 20: Proportion of systematic rating-based components in credit spreads

Table 33: Modified descriptive statistics for sector-based common latent factors

	IN	BF	TL	PW
σ_{Mod}	131.7255	118.1325	152.2141	117.9650
$Skewness_{Mod}$	3.7182	3.7250	4.3269	-1.4426
$Excesskurtosis_{Mod}$	24.9783	13.2727	23.9251	13.8961

$$Excesskurtosis_{Mod} = Kurtosis_{Mod} - 3 \qquad (15)$$

Such a specification focuses on the distribution gap between time series (X_t) and its related median value. Namely, we focus on the risk of deviation from the median value. Notice that for a Gaussian distribution, the median value coincides with the distribution mean. In such a setting, Gaussian skewness and excess kurtosis should be zero for a standard distribution. Corresponding results are displayed for latent factors in tables 33 to 35 for our three considered risk level analyses.

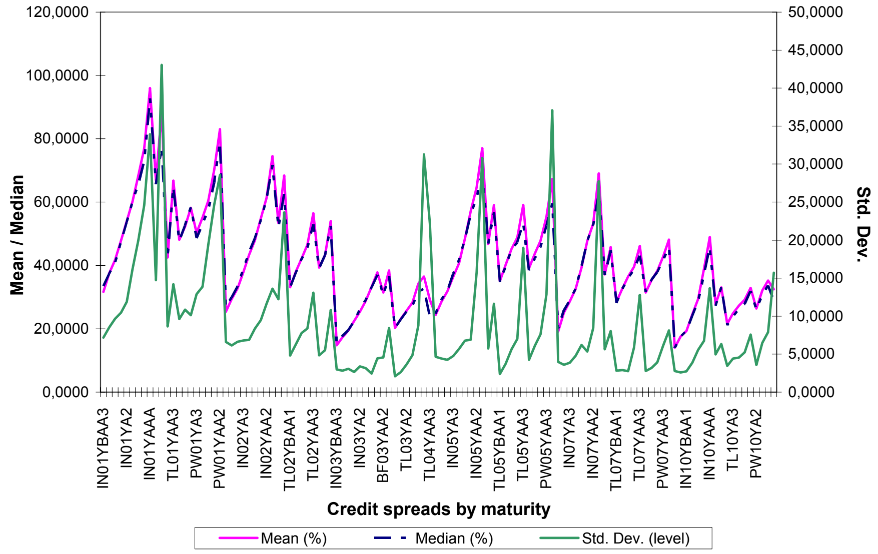

Figure 21: Proportion of systematic maturity-based components in credit spreads

Table 34: Modified descriptive statistics for rating-based common latent factors

Rating	σ_{Mod}	$Skewness_{Mod}$	$Excesskurtosis_{Mod}$
AAA	99.4038	2.0841	23.6365
AA2	83.1024	-4.6217	53.8674
AA3	67.9045	-3.5958	38.3355
A1	104.7644	4.9804	24.4807
A2	45.2868	3.6274	22.9917
A3	71.2459	4.1170	18.7176
BAA1	156.3789	4.9939	28.7179
BAA2	88.3278	4.3576	18.8054
BAA3	86.8026	4.5957	21.5383

Table 35: Modified descriptive statistics for maturity-based common latent factors

Maturity	σ_{Mod}	$Skewness_{Mod}$	$Excesskurtosis_{Mod}$
1Y	121.6354	4.3949	34.8458
2Y	103.3175	4.6554	21.3263
3Y	143.3650	5.2795	30.7976
4Y	79.4652	-0.0069	15.7664
5Y	67.5092	4.6864	22.8581
7Y	61.3891	4.3525	27.3964
10Y	70.2736	1.5695	17.6356
20Y	102.1572	-2.2799	24.0076

With regard to sector analysis, the riskier[22] is TL sector-specific latent factor whereas the less risky is PW sector-specific latent factor. The skewness is generally positive except for PW sector. With regard to rating analysis, the riskier is BAA1 rating grade-based latent factor whereas the less risky is A2 rating grade-based latent factor . The skewness is generally positive except for AA2 and AA3 rating grades. With regard to maturity analysis, the riskier is three-year maturity-based latent factor whereas the less risky is seven-year maturity-based latent factor . The skewness is generally positive except for four- and twenty-year maturities.

6.4 Ultimate common latent factor

Employing Kalman methodology, we extract the ultimate common unobserved component that remains in latent factors. We process to this estimation for each risk level analysis, namely sector, rating and maturity. Specifically, we extract the ultimate common components that result successively from sector-specific latent factors, rating-based latent factors and finally maturity-based latent factors. Hence, we obtain three ultimate common latent components at sector $\left(M_t^{Sector}\right)$, rating $\left(M_t^{Rating}\right)$ and maturity $\left(M_t^{Maturity}\right)$ levels respectively. These three ultimate common latent factors should be approximately the same if the information set that is embedded in each risk level analysis had the same content and significance.

[22] In terms of distribution risk relative to corresponding median value.

In unreported results, we find that all α_M coefficients are above unity (i.e., instable ultimate latent factors over time), and α coefficients are generally significant at a five percent test level and above unity (i.e., latent factors magnify global systematic shocks). The latter comment does not apply to sector analysis insofar as all α coefficients lie between zero and 0.5 and are not significant except for BF sector-specific latent factor. Moreover, the initial variance level P_0 of the ultimate common latent factor is generally insignificant. Furthermore, the dynamic error variance Q_t is insignificant for rating and maturity risk level analyses whereas the initial value M_0 of the ultimate common latent factor is insignificant only for maturity risk level analysis. Finally, resulting ultimate common latent components at sector, rating and maturity levels respectively are right-skewed and exhibit a negative exces kurtosis. Their corresponding median values are very different form their corresponding mean values except for maturity analysis. We also computed corresponding Kendall and Spearman cross correlation coefficients between these three ultimate common latent factors. We find that all the correlation coefficients have a unit value, and are significant at a one percent bilateral test level. Interesting related results are plotted in figures 22 and 23.

Sector-specific, rating- and maturity-based ultimate common latent factors do not have the same level but exhibit the same trend over time. The growth trend is more pronounced for the sector risk level analysis. However, obtained results are not meaningful and conclusive insofar as the resulting ultimate common latent factors are no more than general trends (i.e., straight lines, see figure 22). Especially, we get smooth curves resulting from a loss of sensitivity to economic facts. Using the whole information set in corporate US credit spreads (i.e., aggregating the whole information set across sectors, credit ratings and maturities respectively) yields a loss of sector-specific, rating-based and maturity-based credit spread sensitivity to the financial market and economic cycle. Indeed, we obtain pure evolution trends from which deviations can be of important magnitude. For forecasting prospects, such a level of aggregation seems then unuseful and makes little sense. Moreover, we face seemingly some estimation problems insofar as we cannot stabilize the ultimate common latent factor variances P_t (see figure 23) as initially assumed. Variances P_t tend to increase as we come closer to the end of the business cycle growth trend...

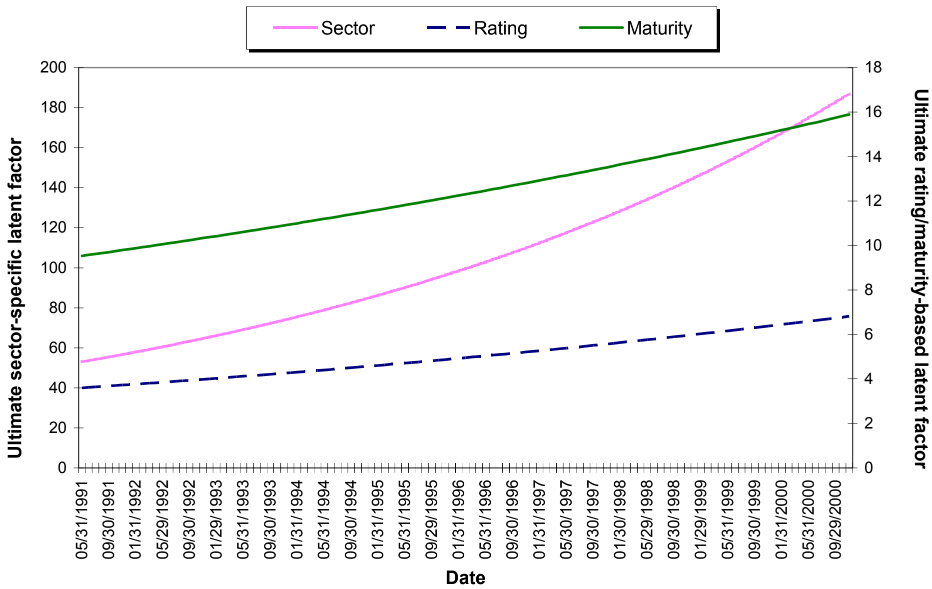

Figure 22: Ultimate common latent factors for sector, rating and maturity analyses.

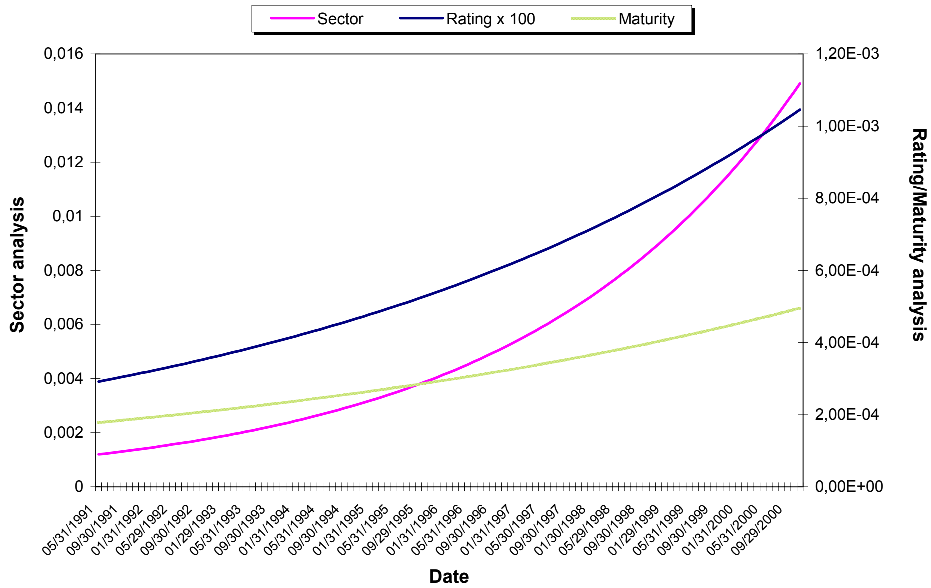

Figure 23: Ultimate latent factor variance P_t for each risk level analysis.

6.5 FLS estimates

We plot the FLS estimates we get for systematic rating- and maturity-based factors in credit spreads. These graphs are in two dimensions over time (see figures 24 to 27).

Obviously, a_t FLS estimate evolutions (i.e., trend of systematic credit spread components over time) are more stable than the evolutions of b_t FLS coefficient estimates over time (i.e., instantaneous link of systematic credit spread components with S&P 500 index return).

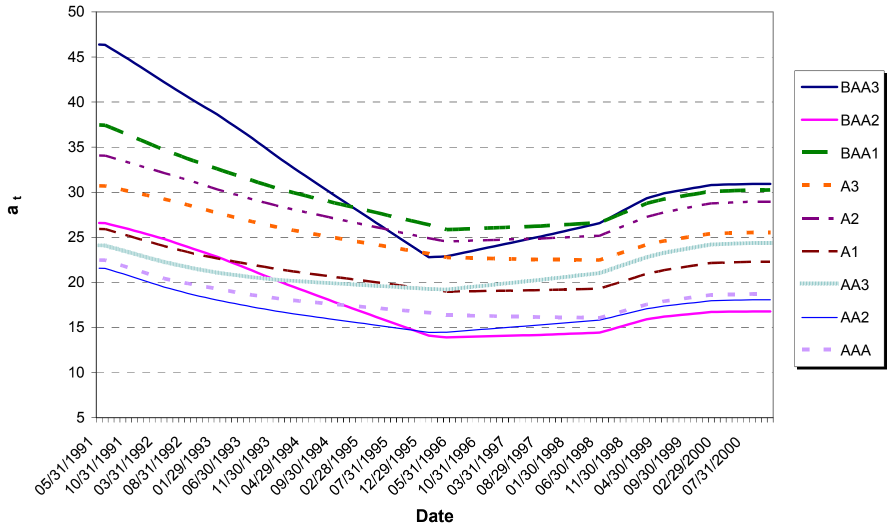

Figure 24: FLS estimates for rating-based systematic factors

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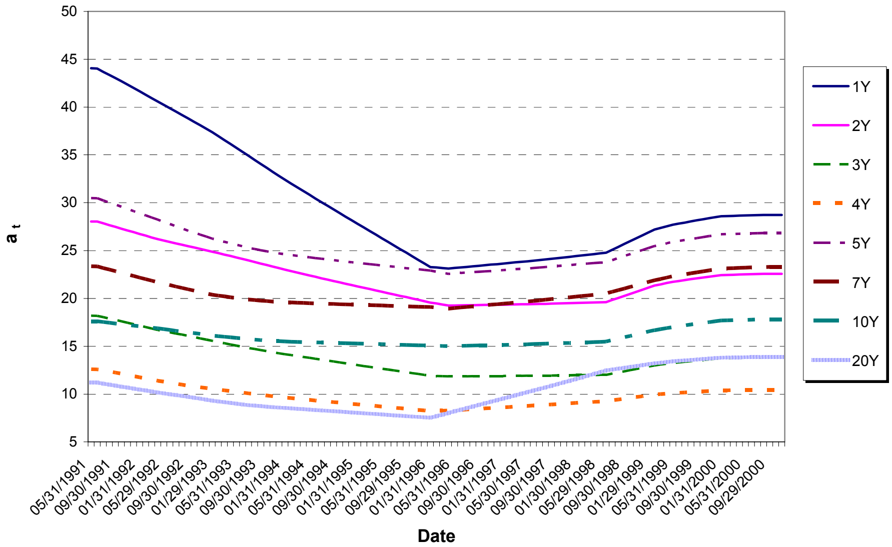

Figure 25: FLS estimates for maturity-based systematic factors

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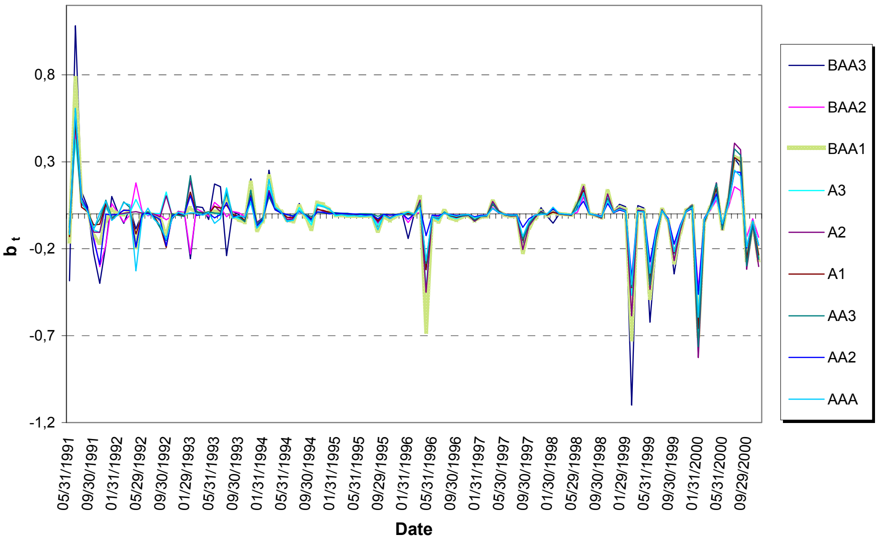

Figure 26: FLS coefficient estimates for rating-based systematic factors

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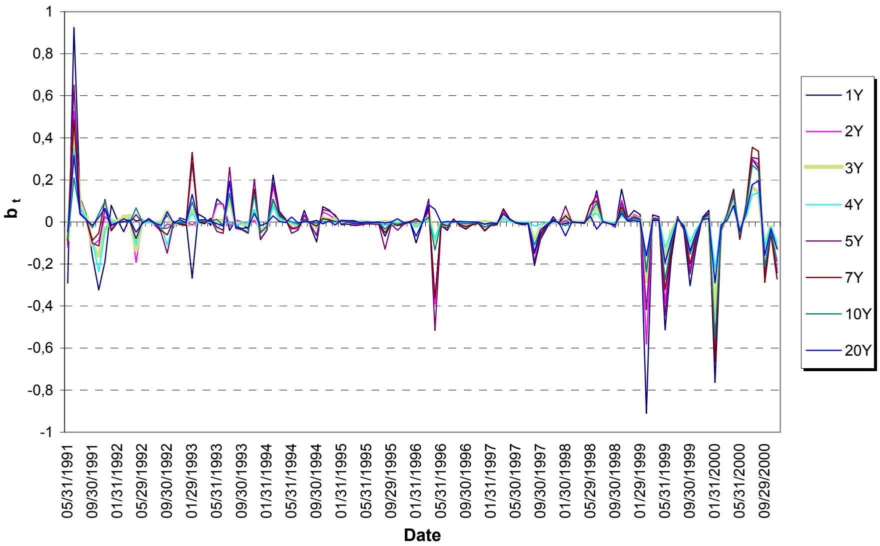

Figure 27: FLS coefficient estimates for maturity-based systematic factors

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