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Relations between Corporate Credit Spreads, Treasury Yields and the Equity Market

Anthony Miloudi[a] and Franck Moraux[b*]
[a] *GSCM-Montpellier Business School*
Membre du CEROM, 2300, Avenue des Moulins
34185 Montpellier Cedex 4, France
a.miloudi@supco-montpellier.fr
[b] *Universite de Rennes 1 and CNDS, Institut de Gestion de Rennes 11 rue Jean Macé*
35000 Rennes, France
franck.moraux@univ-rennes1.fr

ABSTRACT

This paper examines complex relations existing between corporate credit spread indices and the Treasury and Equity markets. A cointegration analysis reveals that a long run relation exists and that some of these connections are credit sensitive. Mainly, it appears that the equilibrium elasticity of credit spread indices to the stock market is a function of the credit risk. Modelling further credit spread dynamics, we find that daily rebalancing of credit portfolios appears justified but the ECM specification suggests that the one-day lagged deviation from the equilibrium relationship has only a limited effect. We finally highlight and discuss the lead-lag structure of markets and the associated causal transmission patterns.

JEL classification: *G32, G12, G14*

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I. INTRODUCTION

Compared to the huge body of theoretical literature, empirical studies on credit spreads appear sparse. A clear understanding of their empirical properties is however necessary for everyone involved in the trading of credit and loan portfolios or concerned about the valuation of credit sensitive instruments such as corporate bonds and credit derivatives. Among the few known empirical results on credit spreads, evidence suggests that they are influenced by few common underlying factors (Pedrosa and Roll, 1998; Collin-Dufresne,Goldstein and Martin, 2001; Christiansen, 2002). In this respect, studying credit spread indices is worthwhile to shed light on the systematic component of corporate credit spreads. A recurrent debate in the empirical literature concerns the way the credit spreads are related to other capital markets. This may come as a surprise for readers because many credit spreads models include a negative correlation with interest rates (e.g., Shimko, Tejima, and Deventer, 1993; Longstaff and Schwartz, 1995a,b; Das and Tufano, 1996;, and Duffie and Singleton, 1999). A closer look appears however necessary because relations between markets appear far more complex than the correlation coefficient may suggest[1].

In this paper we adopt a cointegration framework to explore credit spreads dynamics and assess the existence of long and short run relationships between markets. We differentiate investment grade bonds from speculative ones which represent corporate bonds segments investors can trade[2]. We provide robust evidence that there exist equilibrium relations between markets and that some relationships are credit sensitive. E.g., the equilibrium elasticity of credit spread indices to the stock market appears to be a function of the credit risk. Results of an error correction model (hereafter ECM) conclude that a daily rebalancing of credit portfolios matters but that the one-day lagged deviation from the equilibrium relationship has only a limited effect. By exploring short-run linkages, we highlight the optimal lead-lag structure between markets and causal transmission patterns.

Studying the way credit spread indices behave in relation to other capital markets has several implications for credit management. First of all, our analysis provides direct quantitative outcomes relevant for dynamic portfolio management. Secondly, from a broader viewpoint, our empirical results support current practices and thoughts on the key role of the systematic component in corporate bonds credit spreads. Thirdly, it could be of strategic importance for investors to know how a systematic credit event is conveyed in capital markets and to which extent credit spread indices lead or lag other markets (and in particular the highly liquid stock market). Changes in credit spread indices are commonly used as proxies for variations in investors' perceptions of credit quality. Collin-Dufresne, Goldstein and Martin (2001) claim that hedge funds are sensitive to changes in credit spreads. Finally, such analysis could interest every financial institution involved in corporate credit markets, for at least a couple of reasons. The first issue is related to the Basel 2 capital adequacy requirement since disentangling credit risk dynamics from other market interactions could limit redundant capital charges. The second issue has to do with corporate and human resource management. Financial institutions need appropriate risk-adjusted measures to manage performance of services and, e.g., evaluate corporate bond portfolio managers.

The remainder of this paper is organised as follows. Section II reviews and discusses previous empirical research dealing with relations between corporate credit spread and other markets. Section III presents our data. Section IV questions the existence of an equilibrium relation between markets. Section V focuses on determinants of the credit spread dynamics. Section 6 explores a couple of issues interesting credit portfolio managers i.e. the optimal timing of portfolio rebalancing and the causality structure. Finally, a short section concludes.

II. A LITERATURE REVIEW

As suggested above, there is no clear understanding on the way credit spreads behave in connection to other markets. Part of the perplexity comes from the different streams of research involved. In this section, we discuss empirical studies that question the dynamics of credit spreads and interactions with other markets[3].

The first stream of literature has mainly used regressions to uncover determinants of credit spreads dynamics. A typical example is Collin-Dufresne, Goldstein, and Martin (2001) who explore monthly changes of individual credit spreads. These authors find that variables from other markets have only limited explanatory power. Extracting out and analysing a common factor of these spreads, they highlight so weak relations between markets that they conclude: “there seems to exist a systematic risk factor (…) [for] changes in credit spreads not associated with either the equity or Treasury markets (suggesting a) segmentation of bond and equity markets*”*. Using the same approach, many authors have however found less definitive results on credit spreads *indices*. Duffee (1998) reports, e.g. a negative relationship between credit spread indices of investment grade bonds and the level of interest rates proxied by the three-month Treasury Bill Yield. Brown (2001) explores the changes of non-speculative credit spread indices provided by Salomon Brothers. He finds a significant (and negative) role for the level of the term structure of interest rates. Interestingly, he adds that “the inclusion of two interest variables [among which the slope] has a trivial impact on the exploratory power of the model”. Huang and Kong (2003) consider nine Merrill Lynch corporate indexes that cover both the investment and the speculative ratings. They find that contemporaneous determinants of weekly and monthly changes of credit spreads include variables of the equity market, variables of the term structure of interest rates as well as some macroeconomic indicators.

The second stream of research adopts the cointegration analysis to highlight more complex relations between the Treasury market and the credit spreads. Morris, Neal and Rolph (2000) study monthly data of Moody’s investment grade indices (rated Aaa and Baa) and find that an increase in the 10-year constant maturity Treasury yield causes credit spreads to narrow in the short run while the effect is reversed over the long run. In the same vein, Joutz, Mansi and Maxwell (2002) examine monthly credit spreads indices based on the Lehman Brothers Fixed Income database. Their empirical results testify a negative long run relation between credit spreads and the level of interest rates. They conclude however that there is “a less than straightforward relation between credit spreads and the slope of the Treasury curve”. In the long run, the slope has either a positive or a negative effect and it never impacts on the short run dynamics. They also demonstrate that the excess return on the Market portfolio matters in the short run. Surprisingly, nothing is said on the potential influence of this latter variable in the long run relation.

All these studies have contributed to the understanding of credit spreads. The two last ones need, however, further investigation for several reasons. First, it should be questioned whether the highlighted relations (both in the long-run and the short-run) are robust to periods of time and credit spread indices. Second, both Moody's indexes and the speculative Lehman Brothers Indexes contain callable bonds. Duffee (1998) has demonstrated that these bonds induce a negative relation between credit spreads and interest rates. One can therefore suspect serious biases in previous results. More precisely, the negative sign found in the short run (between Treasury Market and credit spreads) may be either over-estimated or artificially created; while the "long run" positive result may be artificially low. A third issue involves data frequency. Both Morris, Neal and Rolph (2000) and Joutz, Mansi and Maxwell (2002) exploit monthly observations over very long periods (37 years and 12 years, respectively), though they assume that time series are non stationary. As recognised by Joutz, Mansi and Maxwell (2002, p. 9), "it seems implausible that credit spreads are non stationary over long periods of time". Using daily data over a shorter period of time, as Pedrosa and Roll (1998) did, should help in this respect. Monthly data may have "short run" properties not so relevant for credit portfolio managers. Exploiting more frequent data could highlight specific relations and distort (or not) results we have just reviewed. As a final point (not the least one), we claim that it is worth questioning whether the stock market influences credit spreads in the long run.

III. THE DATA

Our database consists of daily observations of a) two Standard & Poor's credit spread indices, b) variables related to the term structure of risk free interest rates and c) the Standard & Poor's 500.

A. The Credit Spread Indices

Standard & Poor's credit spread indices have received little attention although they have been available on a daily basis since 31st December 1998. Huang and Kong (2003) have just (anecdotally) used monthly and weekly observations of these S&P's credit spread indices for robustness checks. S&P's credit spreads indices are average values of credit spreads extracted from quoted prices and pooled by ratings. We denote by IG and SG respectively the investment grade index (BBB and above) and the speculative one (lower than BB). Interested readers are invited to consult the official document (Standard and Poor's (2003)) for details[4].

B. The Exogenous Variables

A couple of variables are used as proxies for the Treasury market behaviour. These are the level and the slope of the term structure of interest rates. The 20-year Treasury bond constant maturity yield is used for the level and the slope is computed as the difference between the 20-year Treasury bond constant maturity yield and the 3-month US Treasury bill. Duffee (1998) has used the short interest rate to proxy the level of the term structure but, recently, Joutz, Mansi and Maxwell (2002) have shown that long-term benchmarks provide more exploratory power in the cointegration vector and the error correction modes. Most of researchers are in accordance concerning the expected effect in the short term of an increase in the spot rate: the credit spreads should narrow. A theoretical reason for this is that a higher spot interest rate means a higher risk neutral drift of the firm's asset value that, in turn, causes a lower default probability and a decrease of the credit risk premium required by investors. Collin-Dufresne, Goldstein and Martin (2001) present arguments that an increase in the slope of the Treasury curve should imply a decrease in credit spreads. The subject is however much debated and deserves more empirical statements before definitive conclusion. Several authors report only limited benefits to include the slope of the interest rates in their analysis (e.g., Collin-Dufresne, Goldstein and Martin, 2001).

As a proxy for stock market behaviour, we use the Standard and Poor's 500 index. The index level reflects the business climate as well as gains anticipated by stockholders. The expected effect of this variable is a negative one: as it rises, the credit spread indices should decrease. Kao (2000) explain that credit spread changes are merely related to small-cap stock indices. So, choosing the Standard and Poor's 500 index is not so favourable for finding a structural relation with the stock market.

C. Some Descriptive Statistics

Our daily data cover the period ranging from 31st December 1998 to the end of January 2004 providing us with a total of 6335 observations. In our study, the period of time has been split into two different sub-periods separated by 11th September 2001 (credit spread indices were unavailable for seven days at that time...). These two periods serve our analysis for robustness checks. For each time series, a total of respectively 675 and 592 observations have been considered in the analysis. This is very similar to Pedrosa and Roll (1998)[5].

Table 1 presents some descriptive statistics over the two sub-periods. Focusing on credit indexes, it appears that the worse the rating, the higher the mean level of credit spreads. In both cases, the credit spreads rise over the two periods (in a different way however). While the way the skewness changes with respect to the rating is in line with previous studies, the presence of extremes (measured by the kurtosis) is not always ranked by rating. In the second sub-period, there are more extremes for the less risky credit spreads index. Both the three-month US T bill and the twenty-year US T bond interest rates have fallen during the second sub-period. The way the average slope of the term structure increases during this period merely indicates that the decrease was dramatic for the short-term level. The Standard and Poor's 500 has also fallen during this period.

When studying empirically the dynamics of credit spreads, a common practice is to use daily changes to remove the unit root problem. In what follows, we pursue the analysis on levels to avoid a loss of information relating to the equilibrium relations between variables (Joutz, Mansi and Maxwell (2002) discuss this point). A transformation is nevertheless desirable because an important feature of the data is the difference in scale of the different variables (in particular the level of the SP500 compared to the credit spread indices expressed in basis points). Both the S&P 500 data and the values of credit spreads are transformed logarithmically[6]. First differences then provide returns that are comfortable to interpret.

Table 1
Descriptive statistics

	IG	SG	SP	USTB	FRCTM	SLOPE
Sub-period 1*						
Mean	180.9	689.7	1339.91	5.04	6.08	1.04
Maximum	254.7	1073.8	1527.45	6.41	6.97	2.43
Minimum	128.9	433.0	1085.79	3.26	5.35	- 0.51
Std. Dev.	38.3	198.0	96.71	0.88	0.39	0.79
Skewness	0.12	0.42	-0.19	-0.22	0.14	- 0.25
Kurtosis	1.57	1.61	2.33	2.02	2.04	2.0
ADF (I(1))	-9.6**	-15.2**	-19.1**	-18.2**	-19.1**	-19.0**
Sub-period 2*						
Mean	215.48	1086.9	999.79	1.38	5.22	3.84
Maximum	283.00	1573.9	1172.51	2.68	6.05	4.61
Minimum	159.80	737.5	776.76	0.79	4.13	2.76
Std. Dev.	29.0	193.0	103.69	0.41	0.41	0.36
Skewness	0.05	0.26	-0.11	0.35	-0.10	-0.39
Kurtosis	2.26	2.20	1.80	2.08	2.51	2.50
ADF (I(1))	-13.7**	-13.8**	-17.9**	-	-17.4**	-16.1**

*The first sub-period ranges from 31st December 1998 to 10th September 2001, the second one from 17th September 2001 to the end of January 2004. USTB and FRCTM stand respectively for the 3-month US Treasury bill and for the 20-year Treasury bond constant maturity yield. IG and SG are expressed in basis point and the interest rates in percentage.. ** Indicates statistical significance at the 0.01 level.

The presence of a unit root is tested to question the intertemporal stationarity of the time series. Based on standard ADF tests, it is shown that all variables[7] are first-order integrated (I(1)) during both sub-samples. Analysis of the price level series reveals non-stationarity for all variables while tests indicate a first-order stationarity, at the 0.01 percent level[8].

The non stationarity of credit spreads indices has already been reported by many authors on different data and periods (e.g., Pedrosa and Roll, 1998; Morris, Neal and Rolph, 2000; among others). Due to the presence of a unit root, care must be taken when analysing the relationship between credit spread indices and other variables. By adopting a cointegration framework, we can circumvent non-stationarity problems and explore safely both long run properties and the short run dynamics of credit spreads.

IV. EQUILIBRIUM RELATIONS BETWEEN MARKETS

This section briefly discusses elements of cointegration analysis and presents our empirical results. We refer to Hamilton (1994) and Johansen (1995) for more details.

A. The Cointegration Analysis

The cointegration analysis questions the existence of long run relations between variables. If answer is positive, there exists a corresponding specification with error correction (Engle and Granger, 1987). This means that dynamics of credit spreads are related not only to some potential exogenous variables but also to the level of disequilibrium in the long term relation (captured by the error correction terms). In other words, the ECM help modelling the way chosen variables influence credit spreads.

The cointegration analysis consists in testing whether time series are cointegrated and whether long-run co-movements exist. It examines whether linear combinations of first-order integrated series are stationary. Denoting *N* the number of variables, the goal is to find some linear relations between first-order integrated variables $X_t = (X_{1,t},...,X_{N,t})$ such that:

$$Z_t = \beta' X_t \tag{1}$$

is a stationary process. Without loss of generality, the associated equilibrium relation between variables may be written $\beta' X_t = 0$. Any satisfying vector, is termed the cointegrating vector. In many cases, this vector may not be unique and the number of vectors is called the cointegration rank. In the present case, however, it is found unique[9]. Note that we follow the Johansen (1991) approach to determine the cointegrating vector.

B. Empirical Results

Table 2 displays the cointegrating coefficients normalised on credit spread indices as estimated by the Johansen (1991) procedure. Observations have been normalised on the credit spreads to emphasise relations with the level, the slope and the log-level of the stock market index. This table demonstrates that equilibrium relations exist between the credit spreads, the S&P 500 and the level and slope of the Treasury term structure. It is important to note that the trace test and the maximal eigenvalue test have been formally run to determine the number of cointegrating rank. Results not provided here (but available upon request) demonstrate (with one exception) that there is at most a single cointegrating vector for each credit class and for each sub-sample[10].

From Table 2, the equilibrium relationship between variables for the first sub period may be written as follows:

$$\begin{aligned} \ln CS_{IG} &= 0.367 \text{ Level} - 0.271 \text{ Slope} - 6.098 \text{ Market} \\ \ln CS_{SG} &= 0.338 \text{ Level} - 0.245 \text{ Slope} - 7.806 \text{ Market} \end{aligned} \tag{2}$$

where "market" stands for the logarithm of the S&P 500. In all cases, *t*-statistics are above critical values provided by Osterwald-Lenum (1992) which account for a deterministic component including a constant and a trend.

It can be observed that all other relations of Table 2 display results that are qualitatively the same. All values are individually significant. This proves that the equilibrium relationship between markets is significant. However, it is worth making some finer comments about each variable.

Table 2
Johansen cointegrating coefficients, normalised on credit spreads

	Level	Slope	Market
Sub period 1			
$\ln CS_{IG}$	-0.367 (-2.347)**	0.271 (4.107)***	6.098 (2.897)**
$\ln CS_{SG}$	-0.338 (-2.571)**	0.245 (4.214)***	7.806 (3.890)***
Sub period 2			
$\ln CS_{IG}$	-0.334 (-7.110)***	0.295 (7.397)***	2.993 (6.966)***
$\ln CS_{SG}$	-0.245 (-5.917)***	0.348 (9.292)***	3.676 (10.38)***
Total sample			
$\ln CS_{IG}$	-0.839 (-3.404)***	0.258 (4.058)***	6.938 (3.799)***
$\ln CS_{SG}$	-0.996 (-3.558)***	0.294 (4.117)***	10.02 (4.530)***

Level and Slope are the variables of the term structure of interest rates Market is proxied by the logarithm of the S&P 500 index. The estimated coefficients in parentheses are *t*-statistics. *** Indicates statistical significance at the 0.01 level. ** Indicates statistical significance at the 0.05 level. The optimal lag structure for each VAR models was selected by minimising the Akaike, the Schwartz Information Criteria and F-statistic. We used the critical values provided by Osterwald-Lenum (1992) to deal with a deterministic component including a constant and a trend.

First, Table 2 displays a significant positive relation between credit spread indices and *the* level of interest rates for both periods. This sign of the equilibrium relation is in line with previous empirical studies. Morris, Neal and Rolph (2000) and Joutz, Mansi and Maxwell (2002) report a positive relation too. On each sub-sample, the investment grade index appears slightly more sensible to the level of the term structure than its speculative counterpart. This is in line with Morris, Neal and Rolph (2000). This property has not been testified by Joutz, Mansi and Maxwell (2002) on their dataset. On the contrary, they found that the strength of the relationship increased as the credit quality declined.

Second, Table 2 offers some clear and significant evidences of a negative relationship between credit spread indices and the *slope* of interest rates for both periods. These results contrast with what Joutz, Mansi and Maxwell (2002) obtain on their data. Their results are not statistically significant in many cases. And they find both positive and negative signs. Finding a negative sign is quite intuitive because of the economic meaning of the slope of the term structure of interest rates. As explained by Collin-Dufresne, Goldstein, and Martin (2001), the slope may be interpreted as an indication of expectations of future short rates but also as an indication of overall economic wealth. In a period of economic strength, one expects credit spreads indices to be low. Empirical results do not permit to conclude on the strength of the relation with regards the credit quality. The equilibrium influence of the slope variable just tends to be of minor magnitude compared to the level's one.

Let's finally turn to the logarithm of the S&P 500 used as a proxy for the Stock Market. Table 2 gives some clear and significant evidence of a negative and strong relationship between credit spread indices and the stock market. Collin-Dufresne, Goldstein, and Martin (2001) have explained that the S&P 500 is an indicator for the business climate. In a period of economic strength, with high levels of Standard & Poor's, credit spreads indexes should be low. The equilibrium relation appears very strong and far stronger than those of the interest rates variables. The elasticity of the credit spread indices on the level of S&P 500 is very large. The sensitivity of the credit spreads to the yield curve is indeed much lower than the one to the stock market. These numerical relations imply that if the SP500's return increases by one point, the credit spreads return will decrease by six or seven basis points during the first sample period and by three or four basis points during the second one. It is interesting to note that the riskier the index, the greater its elasticity with the equity market. In every case, the speculative grade index is more sensitive to this proxy.

The key qualitative result of our cointegration analysis is that there exists a long run relation between markets. As far as we know, such a result is uncommon in the literature and should certainly be confirmed through further research. Another interesting feature is that the structure of the long run relationship is quite similar for each index and that it is robust over different periods.

V. DETERMINANTS OF CREDIT SPREADS CHANGES

The previous section provides evidence of the existence of a long run relation. Some questions now naturally arise regarding whether deviations from this equilibrium have an impact on the short run dynamics, i.e., whether the long run relations (or better deviations from it) belong to the determinants of credit spreads changes. Previous investigations of Morris, Neal and Rolph (2000) and Joutz, Mansi and Maxwell (2002) implicitly suggest significant impacts of the correction on a monthly basis. Due to the daily frequency of our data, its impact may be limited (but without concern about the economic significance of the above equilibrium relationship). This question is of major interest because it provides guidelines for the continuous rebalancing of credit portfolios.

A. Modelling the Returns of Credit Spreads Indexes

Because of the chosen data rescaling, the focus here is on returns of credit spread indices. Many standard variables could have been considered as in Collin-Dufresne, Goldstein, and Martin (2001), but we will avoid such a "kitchen-sink" approach. Rather we focus on the changes of the variables included in the long run relation. Overall, the dynamics of the credit spread indices can be described by:

$$\Delta \ln IG_t = \mu + aZ_{t-1} + b_1\Delta L_t + b_2\Delta S_t + b_3\Delta \ln SP_t + \varepsilon_{IG,t}$$
$$\Delta \ln SG_t = \nu + cZ_{t-1} + d_1\Delta L_t + d_2\Delta S_t + d_3\Delta \ln SP_t + \varepsilon_{SG,t} \tag{3}$$

where Z the equilibrium error is described by equation (1) and μ, ν, a, c and $(b_i)_{i=1,2,3}$, $(d_i)_{i=1,2,3}$ are constant. The significance of a and c is of major importance because they are related to the error correction term induced from the cointegration analysis.

B. Empirical Results

Results for returns of the credit spread indices are displayed in Table 3.

Table 3
Determinants of the credit spreads changes

	Constant	ΔLevel	ΔSlope	ΔMarket	ECT	R²
Sub period 1						
$\Delta \ln CS_{IG}$	0.037 (0.812)	-0.0459 (-5.195)*	0.0161 (2.427)*	-0.1208 (-4.451)*	-0.0010 (-0.801)	0.068
$\Delta \ln CS_{SG}$	0.133 (3.745)	-0.167 (-24.870)*	0.012 (2.391)*	-0.031 (-1.507)	-0.0026 (-3.717)*	0.580
Sub period 2						
$\Delta \ln CS_{IG}$	0.122 (4.708)*	-0.160 (-14.75)*	0.110 (11.30)*	-0.044 (-1.612)	-0.007 (-4.747)*	0.349
$\Delta \ln CS_{SG}$	0.092 (3.887)*	-0.206 (-18.59)*	0.060 (6.012)*	-0.066 (-2.33)*	-0.0003 (-3.920)*	0.593
Total sample						
$\Delta \ln CS_{IG}$	-0.001 (-0.047)	-0.083 (-12.42)*	0.042 (7.502)*	-0.106 (-5.428)*	0.000 (0.042)	0.153
$\Delta \ln CS_{SG}$	0.015 (1.007)	-0.178 (-30.26)*	0.026 (5.454)*	-0.048 (-2.814)*	-0.000 (-0.992)*	0.567

Level and Slope are the variables of the term structure of interest rates. Market is proxied by the logarithm of the S&P 500 index. The estimated coefficients in parentheses are *t*-statistics. Statistical significance is denoted by *, ** for the 99% and 95% confidence levels respectively. The ECT (error correction term) was derived by normalising the cointegrating vector on credit spreads.

From this table, the credit spreads dynamics (and the short-run relationship between markets) for the total sample may be written as follows:

$$\Delta \ln IG_t = -0.001 - 0.083\Delta L_t + 0.042\Delta S_t - 0.106\Delta \ln SP_t + e_{IG,t}$$
$$\Delta \ln SG_t = 0.015 - 0.178\Delta L_t + 0.026\Delta S_t - 0.048\Delta \ln SP_t + e_{SG,t} \tag{4}$$

where e depicts the residue term. These two equations illustrate that the error correction term, while significant statistically, is of minor importance. Interestingly, the different explanatory powers, measured by the adjusted R^2, are higher than those of the previous studies (except during the first sample period for the investment grade index). One finds more than 55% for the speculative case. The explanatory power is systematically and significantly superior for the speculative grade index than for the investment one. This suggests that the chosen variables are more relevant for the speculative index than for the investment one.

The level of the term structure of interest rates appears to be highly significant in all cases. The sign of its coefficient is always negative, implying that the credit spreads fall immediately when interest rates rise. This result is consistent with previous work as mentioned in the introduction. Keeping in mind long run relations, our analysis on daily data confirms the complex relations between credit spreads dynamics and the level of interest rates that have already been reported. At last, it is worth noting that for the level of interest rates, the riskier the index, the higher the sensitivity.

The coefficient of the slope of the term structure of interest rates is also significant in all cases. This result contrasts with previous researches. Collin-Dufresne, Goldstein, and Martin (2001) report that the "slope (is) not very significant either statistically" while no coefficient is significant in the investigation of Joutz, Mansi, and Maxwell (2002) (see their Table 3). The coefficient of the slope is always positive in Table 3. So the credit spreads increase as soon as the slope of the Treasury rises. This effect contradicts the negative long run relation. Overall, influences of the slope are therefore not so straightforward. On the one hand, as an indicator of the economic wealth, when the slope is high, the credit spread indices tend to be low. On the other hand, when the slope increases on a specific day, it immediately causes an increase of the credit spreads. Interestingly, the riskier the index, the lower the sensitivity to the slope of the term structure of the interest rates.

In view of its estimated coefficient, the return of the S&P 500 has a mitigated impact on the short term dynamics of credit spreads when daily data are considered. It is neither systematically significant (unlike Collin-Dufresne, Goldstein, and Martin, 2001) nor ranked by the credit status of the index. As found in previous research, the sign of the coefficient is however negative in every cases. The way the stock market impacts on credit spreads is similar in both the short and long run. At the same time, its relative importance in the short run contrasts with its significant contribution to the long run relation.

The error correction term, though very small, appears significant in some cases. As a result, the long run equilibrium belongs theoretically to the determinants of the credit spread indices. Significant negative coefficients give evidence of a daily adjustment towards the equilibrium relation. The very small absolute values however weaken the importance on a daily rebalancing of credit portfolios for equilibrium purposes.

VI. REMARKS FOR CREDIT PORTFOLIO MANAGERS

Previous sections have direct consequences on the way credit portfolio should be managed. This section investigates further short-run linkages among credit spread indices, the treasury and the stock markets. It aims at studying both the lead/lag structures for an optimal timing of portfolio rebalancing and the causal transmission patterns.

A. Searching for an Optimal Timing of Portfolio Rebalancing

Daily rebalancing of credit portfolios based on contemporaneous determinants of credit spreads has already been considered in a previous section. It is useful, however, to question whether lagged effects may impact. To answer this, a natural approach is to test the lead/lag structure of the short term dynamics. The general specification of the unrestricted VAR to consider is given by:

$$\begin{aligned} \ln IG_t &= \mu + \sum_{i=0}^{N_L} b_{1,i} L_{t-i} + \sum_{i=0}^{N_S} b_{2,i} S_{t-i} + \sum_{i=0}^{N_{SP}} b_{3,i} \ln SP_{t-i} + u_{IG,t} \\ \ln SG_t &= \nu + \sum_{i=0}^{M_L} d_{1,i} L_{t-i} + \sum_{i=0}^{M_S} d_{2,i} S_{t-i} + \sum_{i=0}^{M_{SP}} d_{3,i} \ln SP_{t-i} + u_{SG,t} \end{aligned} \tag{5}$$

The length of the lead / lag structure is then determined by using a couple of tests that are based respectively on a number of information criteria and the Wald statistic. Results corresponding to the Lag Order Selection Criteria and to the Lag Exclusion Wald Tests are displayed in Table 4.

Table 4
The optimal lead/lag structure

	VAR Lag Order Selection Criteria				
	Lag**	FPE	AIC	SIC	HQ
	Sub-period 1				
IG	0	1.32E-07	-4.490393	-4.463389	-4.479931
	1	3.40E-15	-21.96404	-21.82902*	-21.91173*
	2	3.30E-15*	-21.99284*	-21.74981	-21.89868
SG	0	1.15E-08	-6.932354	-6.878348	-6.911431
	1	1.84E-15	-22.57707	-22.41505*	-22.51430*
	2	1.79E-15*	-22.60521*	-22.33518	-22.50060
	Sub-period 2				
IG	0	1.61E-08	-6.594952	-6.565334	-6.583415
	1	1.74E-15*	-22.63519*	-22.48709*	-22.57750*
SG	0	2.26E-08	-6.251761	-6.222142	-6.240224
	1	1.69E-15	-22.66023	-22.51214*	-22.60255
	2	1.53E-15	-22.76262	-22.49606	-22.65879*
	3	1.48E-15	-22.79205	-22.40702	-22.64208
	4	1.47E-15*	-22.80091*	-22.29740	-22.60478

This table displays various information criteria for all lags up to specified maximum. To select the lag order of an unrestricted VAR and respect the principle of parsimony, we proceed as follows. In a first step, we run the VAR with a maximum lag to detect the irrelevant ones. In a second step, we test the obtained VAR system with FPE, AIC, SIC and HQ. * indicates the selected lag from each test at 5% level. For columns 4-7, these are the lags with the smallest value per criterion (FPE: Final prediction error; AIC: Akaike information criterion SIC: Schwarz information criterion and HQ: Hannan-Quinn information criterion). ** There are exogenous variables in the VAR (constant and / or trend), so the lag starts at 0, 1 otherwise.

Table 4 (continued)

		VAR Lag Exclusion Wald Tests				
		IG	LEVEL	SLOPE	MARKET	JOINT
	Sub-period 1					
IG	Lag 1	807.7592* (0.000000)	593.3282* (0.000000)	598.4530* (0.000000)	592.4210* (0.000000)	2722.820* (0.000000)
	Lag 2	4.845638 (0.303506)	4.350774 (0.360610)	2.478011 (0.648578)	2.009294 (0.734049)	21.76181 (0.151050)
SG	Lag 1	680.1263* (0.000000)	608.5298* (0.000000)	640.7618* (0.000000)	604.5703* (0.000000)	2848.554* (0.000000)
	Lag 2	4.642426 (0.325992)	4.695206 (0.320024)	4.197014 (0.379999)	0.654474 (0.956822)	23.62959 (0.097913)
	Sub-period 2					
IG	Lag 1	443.5318* (0.000000)	557.6607* (0.000000)	558.9918* (0.000000)	514.6473* (0.000000)	2176.318* (0.000000)
	Lag 2	26.15284* (0.00000)	2.239471 (0.691810)	3.318677 (0.505979)	2.244342 (0.690920)	41.67075* (0.000442)
SG	Lag 1	664.7808* (0.000000)	570.8878* (0.000000)	571.8527* (0.000000)	541.4605* (0.000000)	2611.814* (0.000000)
	Lag 2	5.116860 (0.275516)	3.189321 (0.526658)	5.349296 (0.253298)	1.156897 (0.885143)	19.08916 (0.264067)

We computed lag exclusion tests for each lag in the VAR (we use until 8 lags for these tests). For each lag, the χ^2 Wald statistic is computed to test the joint significance of all endogenous variables reported in each equation of the VAR model separately (column 1-4) and jointly (last column). * Indicate statistical significance of a Chi-squared test statistics for lag exclusion. Numbers in (…) are associated p-values.

The information based criteria, we use, are the final prediction error; the Akaike information criterion, the Schwarz information criterion and the Hannan-Quinn information criterion. In Table 4, they are denoted FPE, AIC, SIC and HQ respectively and have to be minimized. To select the lag order with these criteria, we proceed as follows. In a first step, we run the VAR with a maximum lag to detect the irrelevant ones. In a second step, we test the obtained VAR system with FPE, AIC, SIC and HQ. Then, we exploit chi-square (Wald) statistics to test i) the joint significance of each of the other lagged endogenous variables in each equation of the VAR model and ii) the joint significance of ALL other lagged endogenous variables in each equation (the last column termed JOINT).

Results of the Lag Order Selection Criteria appear somewhat different depending on the chosen information criteria. However, the lag tends to be one or two periods. In most cases, this lag is one period. A maximum of four lags is found for the speculative grade index in the second sub-period for the FPE and AIC criteria. But this is contradicted by the SIC and HQ criteria. These different results probably come from the main characteristics of each information criterion. Therefore, it seems risky to use these sparse results (see, e.g, Lütkepohl (1991) for more precisions). In order to avoid misspecification, we use a Lag Exclusion Wald test. All these tests indicate an optimal structure of one lag, for each credit spread index and each sub-period.

B. The Causality Structure

The short-run linkage between credit spread indices and markets may be appreciated by the causality structure among variables. One way to address this is to follow Granger (1969). Causality in the Granger sense involves (Chi-square) tests of whether lagged information on a variable Y provides any statistically significant information about a variable X in the presence of lagged X. If not, then "Y does not Granger-cause X.". There are several ways to implement a test of Granger causality, we follow in this study the multivariate VAR approach.

Table 5 reports tests of pairwise causality (between two variables) and joint tests of multivariate causality. Results are very similar when the range of lags varies from one to four days. Granger causality tests are performed using a Chi²-statistic to test the null hypothesis that the first dependent variable series does Granger cause the second, against the alternative hypothesis that the dependent variable does not cause the second.

The first part of Table 5 relates to the period 31/12/1998 to 10/09/2001. Among variables, five significant uni-directional causal links are found (at the .05 level or lower). The speculative grade index is found to be related to the stock market return, the level and the slope of the treasury curve. The speculative grade index seems to dominate other financial variables in term of informational dissemination because it Granger cause all the variables. One possible explanation for this is that during period of tight monetary policy and economic slowdown a number of investors may require higher risk premium from their investment in corporate bonds. So they give some preferences to this specific market.

The second part of Table 5 relates to the period 17/09/2001 to the end of January 2004. It is obvious that, once again, the speculative grade index is the most influential variable. Contrary to the first period, there are feedback effects i.e. a bi-directional causality relations in several pairwise combinations (IG / Level, SG / Slope, Market / Level). During this period, the US short-term interest rate was very low hence increasing the corporate cash flow net of interest rate payments. Corporate bonds trading become good investment opportunities when compared to stocks. It should be noted that our sample period has witnessed many central bank actions in response to major credit or monetary events. More particularly, the Treasury bond buybacks occurred in 2000 as well as the record default following the telecommunication and technology bubble crash during 2002 and 2003. These macroeconomics events could impact on the short-run relationships between the change of credit spreads and the change of other financial markets.

These investigations provide robust and very useful information to improve credit portfolio management. In accordance with previous results, SG and IG are closely related to stock market returns in the short-term, especially for the second sub-period. These strong links could be explained by the fact that stock market returns can be viewed as a proxy for changes in business climate. In a bearing context, most of portfolio managers had to make trade-off between corporate bonds and stocks portfolio allocations.

Table 5
Short-run relationships

	Pairwise Granger Causality / Block Exogeneity Wald Tests			
PANEL A	Sub-period 1			
Dependent Variables*	IG	Level	Slope	Market
IG	-	7.8514 (0.4481)	14.491 (0.0698)	15.093 (0.0501)
Level	7.9787 (0.4355)	-	14.017 (0.0813)	21.287* (0.0064)
Slope	19.350* (0.0131)	12.896 (0.1155)	-	8.8632 (0.3540)
Market	14.938 (0.0604)	7.5659 (0.4770)	6.6060 (0.5797)	-
Joint	47.137* (0.0032)	26.675 (0.3198)	52.498* (0.0007)	47.526* (0.0029)
Dependent Variables*	SG	Level	Slope	Market
SG	-	4.3929 (0.3554)	3.5199 (0.4748)	2.1471 (0.7087)
Level	32.833* (0.0000)	-	4.0172 (0.4037)	10.674* (0.0305)
Slope	22.191* (0.0002)	6.9091 (0.1408)	-	4.7894 (0.3096)
Market	23.238* (0.0001)	6.0038 (0.1989)	2.5041 (0.6439)	-
Joint	61.913* (0.0000)	15.053 (0.2385)	25.173* (0.0140)	28.508* (0.0047)
PANEL B	Sub-period 2			
Dependent Variables*	IG	Level	Slope	Market
IG	-	18.841 (0.0157)	13.336 (0.1008)	6.8254 (0.5556)
Level	66.603* (0.0000)	-	8.6480 (0.3729)	26.832* (0.0008)
Slope	86.545* (0.0000)	6.2427 (0.6201)	-	28.271* (0.0004)
Market	71.102* (0.0000)	17.548 (0.0249)	13.137 (0.1072)	-
Joint	136.39* (0.0000)	32.841 (0.1225)	48.313* (0.0023)	44.459* (0.0067)
Dependent Variables*	SG	Level	Slope	Market
SG	-	10.897* (0.0123)	8.5321* (0.0362)	6.1969 (0.1024)
Level	40.516* (0.0000)	-	3.1302 (0.3720)	12.698* (0.0053)
Slope	31.263* (0.0000)	2.139 (0.5440)	-	11.207* (0.0107)
Market	63.104* (0.0000)	10.101* (0.0177)	4.4329 (0.2183)	-
Joint	90.871* (0.000)	16.242 (0.0620)	25.762* (0.0022)	15.624 (0.0751)

Granger causality tests are conducted by adjusting the long-term cointegrating relationship by the ECM. *Columns 1 to 4 indicate dependent variables in order to our tests indicate Granger causality by row to column and Granger caused by column to row, using a critical value of .05). Figures in bracket are p-values.

VII. CONCLUSION

This paper provides an empirical analysis of the daily Standard and Poor's credit spread indices. Evidence is provided that robust long run relationship exists between each credit spread index and both the Treasury market and the stock market. A second key result is that the equilibrium elasticity of the credit spread indices is a function of credit risk: the lower the rating, the higher the sensitivity to the stock market. Exploring determinants of credit spread returns, it is found that proxies of the Treasury and stocks markets impact the short run dynamics but that the one-day lagged deviation from the long run relation has only a limited effect. Two of tests starting from VAR and VEC models were used to unearth short-run dynamics between credit spread indices and other financial variables. Running a Granger causality analysis, results reveal that credit spread indices contain information on the changes of other financial variables – respectively proxies for the term structure and the stock market. We explain how these results have crucial implications for credit portfolio managers. From purely operational viewpoint, the limited impact of the one-day lagged deviation (from the equilibrium relation) on the short run dynamics weakens long run constraints on the continuous rebalancing of credit portfolios. More broadly, our results may bring to mind strategic choices and tactical asset allocation decisions. The equilibrium relation between capital markets helps to design the long term asset mix of the portfolio. In the short-term, credit portfolio managers have to take into account changes occurring in response to shifts in risk-reward characteristics of different asset classes.

ENDNOTES

1. Joutz and Maxwell (2002) explore other macroeconomic variables beyond the scope of this paper.
2. Credit portfolio managers are usually constrained on a specific segment. E.g., institutional players (pension funds and insurance companies) are used to trade investment grade bonds whereas hedge funds and speculators sometimes favour more risky exposure.
3. Many other kinds of contributions induce information on relations between markets. Typically, to calibrate their theoretical two-factor model, Longstaff and Schwartz (1995a) document a negative correlation between monthly changes of the 30-year government bond yield and monthly changes of credit spreads computed with Moody's corporate bond yield indices. Barnhill, Joutz and Maxwell (2000) explore *yields* of noninvestment grade bond indices. Elton, Gruber, Agrawal and Mann (2001) investigate determinants of the credit risk *premium* of corporate bonds and demonstrate that the Fama-French factors matter. Obtaining a complete view and a clear consensus is rather complex because of the different exogenous variables, database and methodology used. We refer to Kao (2000) for an interesting attempt in this way.

4. We can insist however on a couple of issues. First, these indices are controlled for many different factors such as liquidity, behaviour of the individual issues, representation across ratings and industry sectors, effective durations, etc. Second, only bonds with very exotic particularities are excluded from indices. So these indices retain the maximum information on systematic credit risk. This also means that S&P's keep bonds with well understood optional features and that S&P's account for their embedded options when computing credit spreads. Models and implementation are due to Andrew Kalotay.
5. Pedrosa and Roll (1998) have pooled individual credit spreads on a different and slightly shorter period: 5th October 1995 to 26th March 1997. Their analysis exploits a total of 366 daily observations for each index.
6. This is in line with both Longstaff and Schwartz (1995b) and Pedrosa and Roll (1998).
7. A notable exception is the short term interest rate in the second period. This also explains why we do not retain the short term interest rate as level.
8. We are performing ADF. The lags order in the ADF equations is determined by the significance of the coefficient for the lagged terms corresponding to the AIC minimisation. Intercepts and trends have also been considered. MacKinnon (1991) critical values have been used. The same results are obtained with a Phillips Perron test. All results are available upon request.
9. In all series but the investment grade one over the first sample period. In this special case, one chooses among the alternative cointegrating vectors the one with the most significant coefficients.
10. Both the Schwartz Information Criteria and the Akaike Information Criteria have been used to choose the optimal lag length. Because no significant difference has been found, this strengthens our assumption of a strong underlying structure.

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