ARE CREDIT DEFAULT SWAP SPREADS MARKET DRIVEN?[1]

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Abstract:

We focus on the link prevailing between credit default swap spreads and the U.S. financial market. We apply the Flexible Least Squares regression method to investigate the relationship between CDX spreads and Dow Jones Composite index return. We care about bad scenarii where a decrease in the U.S. market index triggers an increase in CDX spreads…

Keywords: Correlation risk, credit risk, flexible least squares regression, market risk.

JEL codes: C22, G12.

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1. Introduction

Most employed credit risk determinants consist of credit spreads, namely the difference between given corporate yields and corresponding Treasury yields. Basically, credit spreads represent some compensation for the credit risk borne by investors. Such credit risk indicators are shown to be highly correlated with credit default swap (CDS) spreads, which are mainly default risk fundamentals but also liquidity determinants (Longstaff, Mithal and Neis, 2005; Zhu, 2006). Indeed, Blanco, Brennan and Marsh (2005) exhibit and study the equivalence between CDS prices and credit spreads. Moreover, the correlation prevailing between credit risk indicators and equity market determinants has been widely documented (Merton, 1974; Ericsson, Jacobs and Oviedo, 2004; Abid and Naifar, 2006).

In the light of academic and empirical research, we investigate the link prevailing between CDS spreads and Dow Jones Composite index (DJCI) return. We focus on a bad scenario where CDS spreads increase (i.e., an increase in credit risk level, or equivalently a worsening of credit market conditions) when DJCI return decreases (i.e., degradation of financial market conditions, or equivalently an increase in market/systematic risk level).

2. Data

We introduce briefly the data under consideration and some related stylized facts over the studied time horizon.

2.1. Description

We consider daily data ranging from September 20th, 2005 to August 14th, 2006, namely a total of 225 observations per series. We first consider the return of DJCI expressed in basis points (R_DJCI) as a proxy of market/systematic risk factor. Then, we consider a set of eight *Dow Jones CDX indexes* (DJCDX), which are CDS-type indexes tracking the *CDS market* as well as related liquidity side. Specifically, DJCDX indexes are Dow Jones aggregate credit derivative indexes, which represent credit risk fundamentals. The first six indexes under consideration are DJCDX North America credit derivative indexes. They refer to entities (i.e., issuers) domiciled in North America and distributed among five sectors. We label NA_IG, NA_IG_HVOL, NA_HY, NA_HY_BB, NA_HY_B, and NA_XO the investment grade, investment grade high volatility, high yield, BB rated high yield, B rated high yield and crossover DJCDX indexes respectively. Investment grade indexes consider good and higher credit quality reference obligations/credits (i.e., BBB to AAA rated credits with low default risk). High yield indexes consider speculative grade credits, distressed debt as well as some weaker BBB rated credits. Crossover index NA_XO expresses credit rating divergences between Standard & Poor's and Moody's rating agencies across BB/Ba-BBB/Baa rating classes. Finally, the last two indexes under consideration are DJCDX emerging markets credit derivative indexes. They refer to entities domiciled either in Latin America, Eastern Europe, Middle East, Africa or Asia. We label EM and EM_DIV the emerging markets and emerging markets diversified DJCDX indexes respectively. EM index is based on sovereign entities whereas EM_DIV is founded on both sovereign and corporate entities.

Basically, DJCDX credit derivative indexes are equal-weighted indexes except EM index whose weights depend on the CDS IndexCo LLC members' decision. Moreover, CDX indexes are reviewed regularly (i.e., issuers' selection and corresponding reference obligations) and updated on a semi-annual basis (i.e., for a six-month period). Finally, we consider the spreads of DJCDX indexes against appropriate LIBOR rates (see www.markit.com for more details about the aggregation and computation/update process of indexes).[3] Those CDX spreads are expressed in basis points.

2.2. Properties

As regards time series properties, DJCI return and DJCDX spreads are asymmetric and fat-tailed (see Table 1). Indeed, DJCDX spreads are generally leptokurtic except for EM_DIV index case. Moreover, NA_HY index exhibits the highest average DJCDX spread whereas NA_IG index exhibits the lowest one. In unreported results, we computed a one percent Phillips-Perron stationarity test and found a stationary DJCI return and first order integrated DJCDX spreads (i.e., daily index changes are stationary over time).

[Insert Table 1 about here]

[3] All the data analyzed in this applied research paper were initially extracted from Dow Jones Corporation website.

In unreported results, we also computed Kendall and Spearman correlation coefficients between DJCDX spreads and DJCI return. Obtained results are mitigated with regard to their respective sign, and correlation coefficients are insignificant at a five percent bilateral test level. Specifically, only EM, EM_DIV and NA_HY DJCDX indexes exhibit negative correlation coefficients while the other remaining DJCDX indexes exhibit positive correlation coefficients. Moreover, Kendall and Spearman correlation coefficients range from -0.0625 and -0.0941 for EM index (i.e., minimum observed values) to 0.0296 and 0.0454 for NA_HY_BB index respectively (i.e., maximum observed values).

3. Quantitative analysis

We address the following question: How does market risk impair credit risk? We focus specifically on the negative impact of the financial market on corporate credit market (Gatfaoui, 2005). For this purpose, we run Flexible Least Squares (FLS) regressions of observed DJCDX spreads on observed DJCI returns over the time horizon under consideration.

3.1. Econometric Study

The FLS regression method was formerly introduced by Kalaba and Tesfatsion (1988, 1989). Such an econometric method allows for running regressions with time-varying parameters, capturing then some instantaneous link between random variables. Moreover, this methodology is robust to outliers, nonstationary data as well as correlated data among others. We apply FLS method to run regressions of a given DJCDX spread '*S*' on DJCI return:

$$S_t = a_t + b_t \times \text{R\_DJCI}_t + v_t \qquad (1)$$

where time t ranges from 1 to 225, a_t and b_t are time-varying regression coefficients and v_t is a residual measurement error. Coefficient a_t represents the DJCDX spread component that is unexplained by DJCI return (i.e., idiosyncratic/unsystematic trend over time) whereas b_t coefficient catches the dynamic link between DJCDX spread and DJCI return (i.e., instantaneous correlation risk indicator). Given optimal cost parameters c_1 and c_2, we target then to minimize the following objective function F:

$$F(a_t, b_t, t = 1 \cdots 225) = \sum_{t=1}^{225} v_t^2 + c_1 \sum_{t=2}^{225} (a_t - a_{t-1})^2 + c_2 \sum_{t=2}^{225} (b_t - b_{t-1})^2 \qquad (2)$$

The lower cost parameters are, the more volatile time-paths of related regression coefficients are.[4] Conversely, the higher cost parameters are, the smoother (i.e., more regular and stable) corresponding coefficients' time-paths are.

3.2. Results

The corresponding obtained cost parameters are listed in Table 2 below. Regression trend coefficients a_t are stable (see Figure 1) over time whereas b_t slope coefficients are highly volatile over time (see Figure 2). As a result DJCDX spreads exhibit a stable default component (i.e., a stable

[4] In such a case, time-variation in regression parameters is weakly penalized whereas it becomes strongly penalized in the converse case.

unsystematic/idiosyncratic component) whereas they exhibit an extremely volatile market-based component (i.e., systematic/market component). In unreported results, we checked for stationary and white noise patterns in regression residuals while estimating simple and partial autocorrelations as well as Phillips-Perron and Ljung-Box statistics. Briefly, residuals are stationary and behave like a white noise process over time.

[Insert Table 2 about here]

[Insert Figure 1 about here]

With regard to Figure 1, NA_IG index exhibits the lowest unsystematic component over time whereas NA_HY exhibits the highest one. Moreover, idiosyncratic CDX spread components tend generally to decrease until the end of the first quarter 2006 and start increasing during the second quarter 2006 (i.e., higher default risk level). Generally speaking, default risk level (i.e., idiosyncratic CDX spread component) is lower at the end of the studied time horizon than at its beginning.

[Insert Figure 2 about here]

With regard to Figure 2, the link prevailing between CDX spread levels (i.e., credit risk fundamental) and DJCI return level (i.e., market risk proxy) illustrates the dependence of credit risk relative to market risk. Our main focus being to quantify the joint credit risk and market risk evolution, we focus on the sign of b_t regression coefficients. Specifically, when b_t regression coefficient is negative, this means that

DJCDX spread increases when DJCI return decreases, and conversely.[5] In the worst case, credit risk increases (through CDS spreads' widening) when market risk increases (through DJCI return's tightening). To get a view, we compute the proportion of positive and negative values of b_t coefficients over our studied time horizon for each DJCDX index (see Figure 3).

[Insert Figure 3 about here]

In unreported results, we computed Spearman correlation coefficients between first order differences of DJCDX spreads (i.e., daily variation $\Delta S_t = S_t - S_{t-1}$) and first order differences of DJCI return (i.e., daily change ΔR_DJCI_t). All correlation coefficients are negative and significant at a one percent bilateral test level. Therefore, DJCDX spreads and DJCI return tend generally to evolve in an opposite way over the time horizon under consideration. Moreover, previous correlation coefficients range from -0.3584 level for EM index to -0.1541 level for NA_HY_BB index. As an extension, we also considered the joint evolution of first order differences of both DJCDX spreads and DJCI return (see Table 3). Indeed, Table 3 considers the respective signs of the first order differences of both DJCDX spreads and DJCI return, and summarizes the cases where those signs are identical and reverse as compared to the total number of observed cases (i.e., a total of 224 observations for first order differences time series). The proportion of simultaneous reverse changes in both ΔS_t and ΔR_DJCI_t is far above the proportion of

[5] Namely, a negative slope coefficient illustrates an opposite simultaneous evolution of both DJCDX spreads and DJCI return.

simultaneous correlated changes in both ΔS_t and ΔR_DJCI_t. The lowest and highest rate of correlated joint daily variation is 33.9286% and 45.5357% for EM and NA_HY_BB indexes respectively whereas the respective lowest and highest rate of converse joint daily variation is 53.5714% and 65.6250% for NA_HY_BB and EM indexes respectively. Such a feature confirms the general worst case-joint trend for credit and market risks over the studied time horizon. Therefore, market risk tends to impair credit risk over the time horizon under consideration.

[Insert Table 3 about here]

4. Conclusion

Resorting to FLS regression method, we exhibited the dynamic link prevailing between DJCDX spreads and DJCI return. Indeed, the time-varying trend coefficient illustrates idiosyncratic DJCDX spread components whereas the time-varying slope coefficient reflects the instantaneous correlation risk between credit risk and market risk over time. We also quantified the joint evolution of credit risk and market risk over our studied time horizon. First, we found stable positive unsystematic/idiosyncratic DJCDX spread components over time. Second, the link prevailing between DJCDX spreads and DJCI return was extremely volatile and exhibited frequent sign changes over time (i.e., unstable correlation risk). Therefore, the dependence structure between credit risk (i.e., DJCDX spreads) and market risk (i.e., DJCI return) is proved to be time-varying and highly volatile. Finally, we found a general negative link prevailing between credit risk and market risk over the time horizon under consideration (i.e., aggregate static view). Further extension should however study such a dependence structure in a two-dimension setting (i.e., more accurate bivariate setting assessing the simultaneous correlation risk). Such an assessment task could easily be handled in a multivariate distribution setting or in a copula-based modeling framework for example (Cherubini, Luciano and Vecchiato, 2004).

References

Abid F., and N. Naifar (2006). The Determinants of Credit Default Swap Rates: An Explanatory Study. International Journal of Theoretical and Applied Finance, 9 (1), 23-42.

Blanco R., Brennan S., and I.W. Marsh (2005). An Empirical Analysis of the Dynamic Relation Between Investment-Grade Bonds and Credit Default Swaps. Journal of Finance, 60 (5), 2255-2281.

Cherubini U., Luciano E., and W. Vecchiato (2004). Copula Methods in Finance. John Wiley & Sons, Chichester.

Ericsson J., Jacobs K., and R.A. Oviedo (2004). The Determinants of Credit Default Swap Premia. Working paper, CIRANO, Montreal, 2004s-55. Forthcoming in the *Journal of Financial and Quantitative Analysis*.

Gatfaoui, H. (2005). How Does Systematic Risk Impact U.S. Credit Spreads? A Copula Study. Revue Banque & Marchés, 77 (July-August), 5-16.

Kalaba R., and L. Tesfatsion (1989). Time-Varying Linear Regression via Flexible Least Squares. Computers and Mathematics with Applications, 17 (3), 1215-1245.

Kalaba R., and L. Tesfatsion (1988). The Flexible Least Squares Approach to Time Varying Linear Regression. Journal of Economic Dynamics and Control, 12 (1), 43-48.

Longstaff F.A., Mithal S., and E. Neis (2005). Corporate Yield Spreads: Default Risk or Liquidity? New Evidence From the Credit Default Swap Market. Journal of Finance, 60 (5), 2213-2253.

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. Journal of Finance, 29 (2), 449-470.

Zhu, H. (2006). An Empirical Comparison of Credit Spreads Between the Bond Market and the Credit Default Swap Market. Journal of Financial Services Research, 29 (3), 211-235.

Figures

Figure 1: FLS Regression Trend

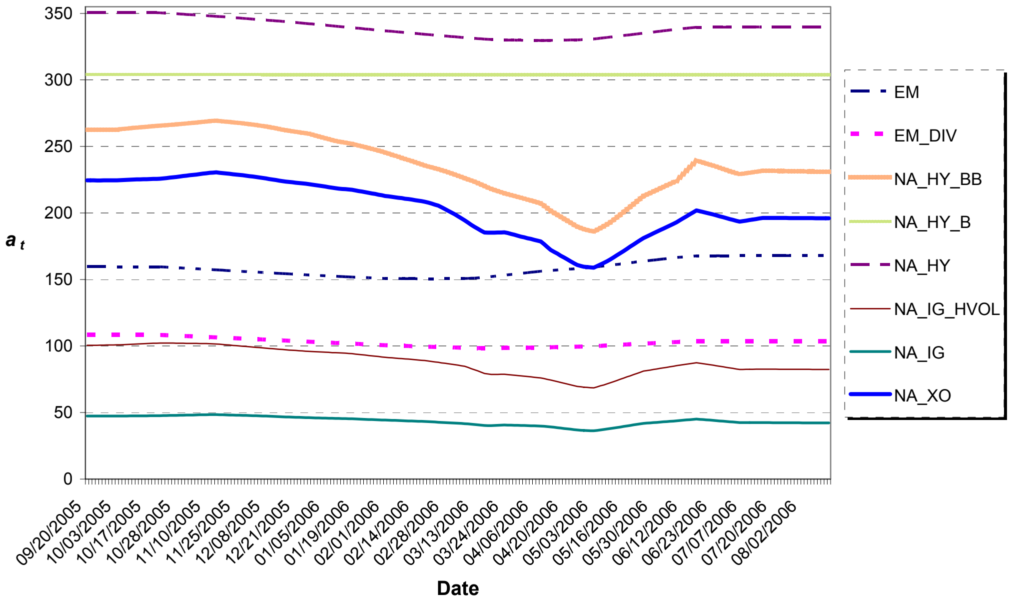


Figure 2: FLS Regression Coefficient

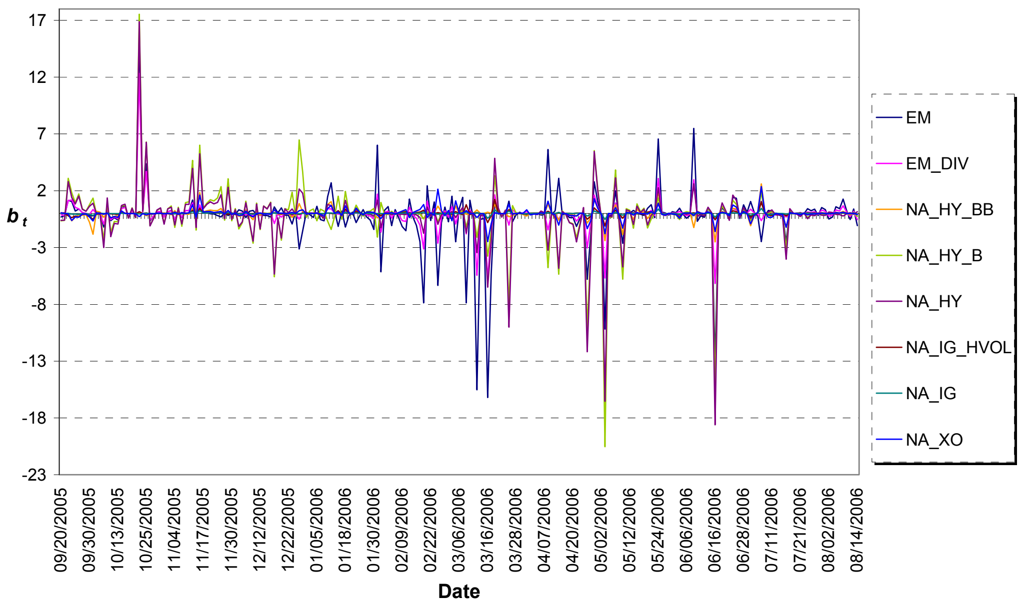
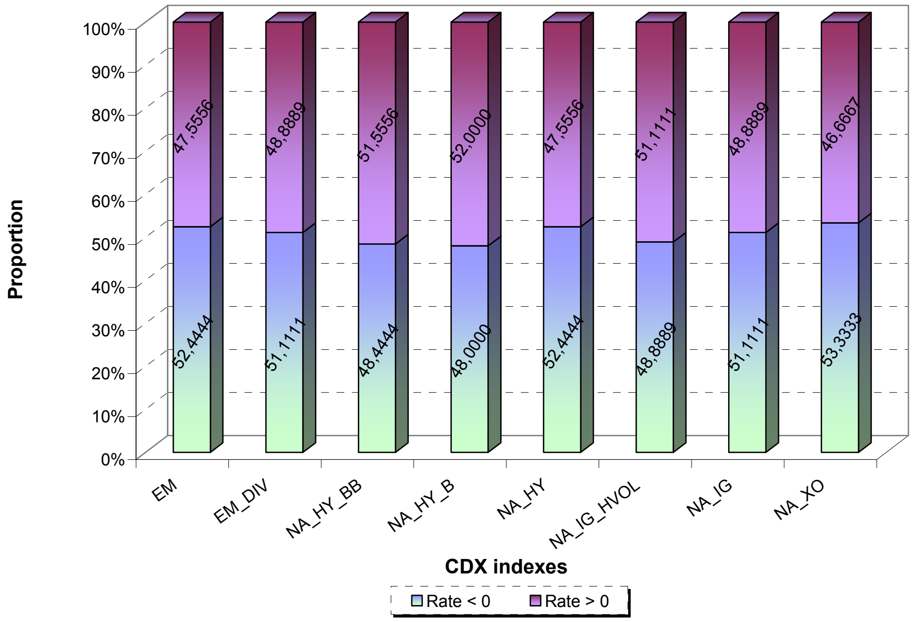


Figure 3: Proportions of Positive and Negative b_t Coefficient Values



Tables

Table 1: Descriptive Statistics for CDX Spreads and DJCI Return

Index	Mean	Median	Std. Dev.	Skewness	Excess kurtosis
EM	154.0639	154.7300	27.8717	-0.1584	-0.4742
EM_DIV	102.9907	102.1300	15.4991	0.7123	0.7566
NA_HY_BB	237.0725	240.4400	27.4675	-0.3275	-0.6396
NA_HY_B	313.9764	310.6200	26.9951	0.0117	-0.3855
NA_HY	348.1687	344.1000	32.8510	0.4284	-0.1431
NA_IG_HVOL	88.5607	89.1900	10.7279	-0.1817	-0.9118
NA_IG	43.7473	44.2200	3.7758	-0.2183	-0.5853
NA_XO	204.2981	211.5600	24.3584	-0.3938	-0.7453
R_DJCI	3.5220	6.5810	80.0253	0.1164	0.4459

Table 2: Cost Parameters

Index	c_1	c_2
EM	0.1000	0.0010
EM_DIV	0.1000	0.0010
NA_HY_BB	0.0010	0.0010
NA_HY_B	10.0000	0.0010
NA_HY	0.1000	0.0010
NA_IG_HVOL	0.0010	0.0010
NA_IG	0.0010	0.0010
NA_XO	0.0010	0.0010
R_DJCI	0.0010	0.0010

Table 3: Proportions for Joint Changes In CDX Spreads And DJCI Return

Percentage	Correlated behavior			Reverse behavior		
	CDX spreads increase and DJCI return increases	*CDX spreads decrease and DJCI return decreases*	*Sum*	*CDX spreads increase and DJCI return decreases*	*CDX spreads decrease and DJCI return increases*	*Sum*
EM	12.5000	21.4286	33.9286	31.2500	34.3750	65.6250
EM_DIV	16.5179	25.0000	41.5179	27.2321	30.8036	58.0357
NA_HY_BB	18.7500	26.7857	45.5357	25.4464	28.1250	53.5714
NA_HY_B	15.6250	28.1250	43.7500	24.1071	31.6964	55.8036
NA_HY	15.6250	25.8929	41.5179	26.3393	31.6964	58.0357
NA_IG_HVOL	18.3036	24.1071	42.4107	28.1250	29.0179	57.1429
NA_IG	15.6250	25.0000	40.6250	27.2321	31.2500	58.4821
NA_XO	16.9643	24.5536	41.5179	28.1250	29.9107	58.0357