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Credit Spread Modeling: Macro-financial versus HOC Approach

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ABSTRACT *– The aim of this paper is to throw light on the relationship between credit spread changes and past changes of U.S. macro-financial variables when invariants do not have Gaussian distribution. The first part presents the empirical analysis which is based on 10-year AAA corporate bond yields and 10-year Treasury bond yields. Explanatory variables include lagged U.S. leading index, Russell 2000 returns, BBB bond price changes interest rate swaps, exchange rates EUR/ USD, Repo rates, S& P 500 returns and S&P 500 volatility, Treasury bill changes, liquidity index-TRSW, LIBOR rates, Moody's default rates; credit spread volatility and Treasury bills volatility. The proposed dynamical model explains 73% of the U.S. credit spread variance for the period 1999:07-2013:07. The second part of the article introduces the parameter estimation method based on higher order cumulants. It is demonstrated empirically that much of the information about variability of Credit Spread can be extracted from higher order cumulant function (85%).*

KEY WORDS*: Credit Spread Modeling, ARMA Parameter estimation, Higher Order Cumulants, Non Gaussian ARMA models, Dynamic regression*

Introduction

The predictability of credit spread has been assuming a new importance since both fixed income investors and financial managers need reliable predictions to make more money. For the past fifteen years, the source of the greatest variance between investment objectives and payoffs has been credit risk.

There are two opposed micro-financial approaches to credit spread modeling, used in literature so far: the "structural" approach versus the "reduced" approach. However they have a common characteristic, which is the assumption that the main explanatory component of credit spread is a default risk. The market pricing of default risk can be analyzed using the "structural approach", (Merton, 1974), which is based on Black and Scholes option pricing model.

The "reduced approach" to the pricing of default risk assumes that investors require excess return in order to cover the risk. In this context the pricing requires a measure of corporate default probability and the associated recovery rates. Although conceptually very elegant, the structural models have had limited success in matching with empirical data.

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Elton, Gruber and Mann [2001] found that expected default losses are insufficient to explain the great part of the variability of credit spreads. Using a reduced form model, they showed that the expected default loss can explain only up to 25% of credit spread. Huang and Huang (2003) used a structural model too, and verified that for investment grade bonds (Baa and higher rating) only 20% of the spread is explained by the default risk. Both models used historical default frequencies produced by Moody's and Standard and Poor's.

Alternative estimates of default probabilities are provided by Lando and Skodeberg (2002) who used a continuous time analysis of rating transitions to improve the estimate of the default risk. Collin-Dufresne, Golden and Martin (2001) examined a firm level related risk as determinants of credit spread changes, spot rate changes, changes in the slope of the yield curve, changes in a firm leverage, changes in volatility, changes in the probability and magnitude of a large negative jumps. They concluded that the monthly changes in firm specific factors are not a driving force in credit spread changes.

Besides Merton (1974), Krishman, Ritchken and Thompson (2003), showed that the predictability of credit spread, based on the credit slope, largely depends on the maturity of the corporate bonds.

Zhang, Zhou and Zhu (2005), argued that the unsatisfactory performance of structural models may be in part attributed to the fact that the impact of volatility and jump risks are not treated seriously. They found strong volatility and jumps effects, which predict another 16% of credit spread.

In this paper, it is first investigated how credit spread changes are explained by the changes of macro-financial variables such as: lagged changes Russell 2000 returns, BBB bond price changes, U.S. leading index, interest rate swaps, exchange rates EUR/USD, Repo rates, S& P 500 returns and S&P 500 volatility, Treasury bill changes and their volatility, liquidity index and Moody's default index (Section 1). Empirical dynamic regression model is discussed in section two.

Statistically speaking, Credit Spreads Time Series is non Gaussian which means that its autocorrelation function does not provide sufficient statistics for ARIMA-GARCH parameter estimation. Cumulants (in frequency domain called polyspectra) have received the attention of the statistics and signal processing and wireless communications (Zou, Zhong & Jiang ,2013). Gianninakis (1990) derived cumulant based ARIMA order determination method for communication signals, because second order cumulants for non Gaussian signals vanish, higher order cumulants are generally nonsymmetrical functions of their arguments, and as such carry phase information about ARMA parameters.

The section three of this article discusses some of the theory behind higher-order statistics, particularly as it applies to non Gaussian signals ARMA parameter estimation. It then in details describes the steps taken towards constructing such an estimator. These steps are aimed to determine the Credit Spread ARMA model order which is necessary to provide accurate cumulant estimates using Mathlab software, to examine the performance of a cumulant based ARMA parameter estimation for a non-Gaussian Credit Spread time series, and to examine the ability of the cumulant based model to outperform the classical regression model. Conclusion is given in section four.

The problem and the methodology

It is well known that a credit spread represents the difference between the yield of a risky security (corporate bond) and that of a risk-free security of the same or similar maturity. The predictability of a credit spread is of paramount importance for both fixed income investors and financial managers.

If prediction shows that the future credit spread will widen, the trader would sell the portfolio of corporate bonds and vice versa.

On the other side, corporate finance managers would be able to lower the firm's cost of capital by timing debt issuance. As pointed out by Harvey (1999), if prediction is that credit spread will tighten, managers will support short term debt operations, will lock in interest rates today and wait until the spread really tightens to issue long term debt.

The static multiple regression model for credit spread, as used almost everywhere, is not considered. Instead, Multiple Integrated Autoregressive IA –GARCH model is used.The rational for this choice is quite simple: the classical multiple regression model reflects instantaneous relationship. Thus, even when the coefficient of determination is high, this model is of little use for forecasting whether statistically significant predictions of explanatory variables are not available.

Almost all explanatory variables used in literature so far, after being stationarized by making their first differences, have quickly vanishing autocorrelations which contain a marginal amount of information useful for their forecasting.

Let X_{it} and Y_t be jointly stationary Gaussian processes with finite first and second moments that can be treated as outputs from the linear Autoregresssive Integrated Moving Average (ARIMA) filters, whose inputs are white noise signals: u_{ti} and v_t respectively:

$$A1(Z)^* DX_{ti}= B1(Z)^* ui_t, \quad i=1,2\ldots k$$
$$A2(Z)^* DY_t= B2(Z)^* v_t,$$

where Z is a backward shift operator:

$$Y_{t-1}=ZY_t\,,\; Y_{t-k}=Z^kY_t\,;$$

$A(Z) = 1\text{-}a_1Z\text{-}a_2Z^2 - \ldots a_pZ^p$ and $B(Z) = 1\text{-}b_1Z\text{-}b_2Z^2 - \ldots b_qZ^q$ are AR and MA filters of orders p and q respectively, D is the first difference filter, $DY_t = Y_t - Y_{t-1}$, i is the index of independent variable, k is the number of independent variables. The model of credit spread we use has IAR-GRACH general form, as defined by Box-Jenkins (1976) and by Bollerslev (1986), as a generalization of Engle (1982). IAR model has the form:

$$DY_t =\sum_{j=1}^{k}\sum^{pi}\alpha_{ij}{}^*x_{ti-j} + \sum_{m=1}^{q}\beta_m{}^*\varepsilon_{t-m}\,, \qquad (1)$$

i=1,2...pi, j=1,2…k, m=1,2…q ,

while GARCH model is :

$$h_t = \omega + \gamma h_{\tau-1}\varepsilon^2_{t-1} + \delta h_{t-1} \quad (2)$$

where pi is the AR order or the series i, i is the index of independent variables and ε_t is the residual white noise associated with Y_t, q is the MA order of the $\{\varepsilon_t\}$ residuals and $\{h_t\}$ is volatility of the residuals.

Dynamic Macro-Financial model

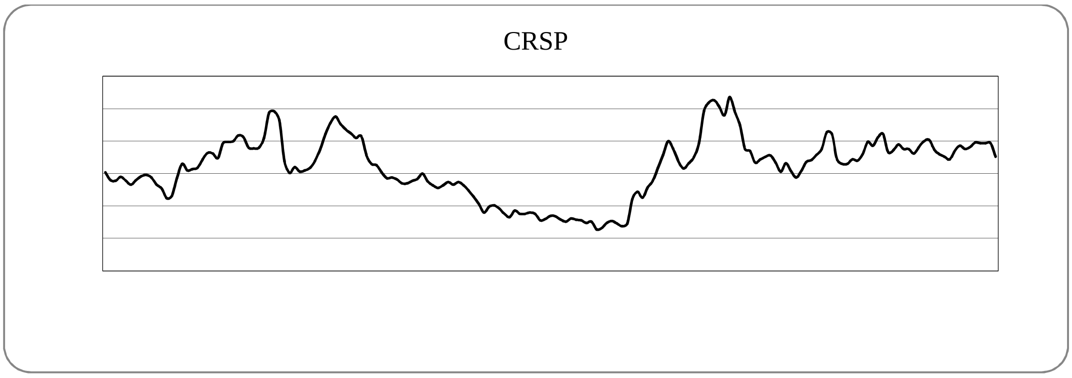
The corporate credit spread, or just the credit spread CRSP, is usually measured as the difference between the yields of a defaultable corporate bond and of a U.S. government bond of comparable time to maturity. In this article, the Credit Spread is the difference between yields of 10 year AAA bonds and 10-year Treasury bonds. Its chart is presented in Figure 1, for the period 1999:01-2014:07.

A statistical description for AAA yields, 10-year treasury yields and the credit spread, are presented in Table 1.

Table 1. Descriptive statistics for Credit Spread

	DCRSP	AAA	TRE10Y
Mean	-0.000402	7.080172	5.781264
Median	0	7.17	5.81
Maximum	0.41	9.01	8.28
Minimum	-0.64	4.96	3.33
Std.Dev.	0.116715	0.960916	1.1809
Skewness	-0.405155	-0.232654	0.06616
Kurtosis	8.569198	2.456881	2.156968
Observatior	174	174	174

Figure 1. Credit Spread chart



The Credit Spread appears to be non -stationary, which is demonstrated by using the unit root test results:

ADF Test				
Statistic	-2.20972	1%	Critical Value*	-3.47
		5%	Critical Value	-2.878
		10%	Critical Value	-2.576
*MacKinnon critical values for rejection of hypothesis of a unit root.				

The first difference of the credit spread has autocorrelations (AC) and partial autocorrelations (PAC) different from zero, as presented in Table 2.

Table 2. Autocorrelations (AC) and partial autocorrelations (PAC)

Lags	1	2	3	4	5	6	7	8	9	10
AC	0.348	-0.06	-0.125	-0.184	-0.128	-0.009	0.007	0.03	-0.014	-0.061
PAC	0.348	-0.21	-0.033	-0.157	-0.029	0.008	-0.043	0.01	-0.066	-0.042

The best time series model obtained by using AIC criterion is ARIMA (2,1,0) with coefficients presented in Table 3. As it can be seen from the table, this model explains only 16.25% of the credit spread variance.

Table 3. ARIMA model

Dependent Variable: D(CRSP)				
Included observations: 172				
Variable	Coefficie	Std. Error	t-Statistic	Prob.
AR(1)	0.42333	0.074555	5.67813	0
AR(2)	-0.2072	0.07458	-2.7778	0.0061
R-squared	0.16245	Mean dependent v		0.0003

Explanatory variables

As mentioned above , the following explanatory variables are used : S&P 500 composite index returns and its volatility, three months Treasury Bill rate and corresponding volatility, Libor rate, Repo rate, Swap rate, Russell 2000 index, EUR/USD exchange rate, liquidity index and U.S. Leading Index. Their meanings are explained bellow.

By using the unit root test, it is shown in Table 4, with 99% confidence, that all the variables are non stationary, whilst S&P 500 returns, Russell 2000 returns and U.S. leading index are stationary time series.

The S&P 500 is one of the most commonly used benchmarks for the overall U.S. stock market. It is a market-value weighted index, which means each stock's weight in the index is proportionate to its market value. S&P 500 returns are calculated as usually:

$$SP500Rt= (SP(t)-SP(t-1)) /SP(t-1) \quad (3)$$

Table 4. Unit root test

Augmented Dickey-Fuller Test Results	
Variable	ADF Test Statistic
1% Critical Value*	-3.472
5% Critical Value	-2.880
10% Critical Value	-2.576
SP500r	-6.527
TRE3M	-1.905
SWAP5	-2.194
SWAP10	-2.042
USLEAD	-4.762
RUSSEL2000	-7.253
EURO	-1.489
DEFAULT RATE	-1.791
LIBOR6M	-1.881
TRSW	-1.868
REPORATE	-2.132
PRIME RATE	-1.959
*MacKinnon critical values for rejection of hypothesis of a unit root.	

Stock market returns are expected to be negatively correlated with bond market returns. The best ARMA model is ARMA (1,1) whose coefficients are presented in Table 5.

Table 5. ARMA (1,1)

Dependent Variable: SP500R				
Included observations: 164				
Variable	Coefficie	Std. Error	t-Statistic	Prob.
C	0.0080	0.0033	2.4567	0.0151
AR(1)	-0.6321	0.2498	-2.5301	0.0124
MA(1)	0.6760	0.2454	2.7545	0.0066
R-squared	0.0346	Mean dependent v		0.0081

Three months Treasury Bill rate, *T Bills*. By definition, this rate is a debt obligation issued by the U.S. government and backed by its full faith and credit, having a maturity of one year or less. Treasury Bills are considered the safest securities available to the U.S. investor, and so the yield of these securities is considered risk-free.

These securities do not pay a coupon, and the interest earned is estimated by taking the difference between the par value and the purchase price of the bond, with time adjustments.

In this analysis the T-bills with 3 months maturities are the only T bills that are significant for credit spread variations.

Their best ARIMA model is presented in Table 6. As it can be seen from the table the series has significant volatility of the GARCH (1,1) residuals.

Interest rate Swaps can provide forward indication of credit spread direction. Interest rate swaps are used to hedge interest rate risks as well as to take on interest rate risks. If a treasurer is of the view that interest rates will be falling in the future, he may convert his fixed interest liability into floating interest liability; and also his floating rate assets into fixed rate assets. If he expects the interest rates to go up in the future, he may do vice versa (the floating side of the swap would usually be linked to another interest rate, often the LIBOR). In an interest rate swap, the principal amount is never exchanged; it is just a notional principal amount. In a word, interest rate swaps are financial tools that potentially can help issuers to lower the amount of debt service. We use two SWAP indexes, which are significant for the credit spread changes: a 5-year SWAP and 10-year SWAP index, taken from Bloomberg.

Table 6. ARIMA model

Dependent Variable: D(TRE3M)				
	Coefficie	Std. Error	z-Statisti	Prob.
AR(1)	0,9074	0,046431	19,543	0
MA(1)	-0,6521	0,08504	-7,6682	0
	Variance Equation			
C	0,00428	0,001808	2,36827	0,0179
ARCH(1)	0,2094	0,059513	3,51855	0,0004
GARCH(1)	0,65998	0,082713	7,97914	0
R-squared	0,24012	Mean dependent v		-0,0164

The best ARMA-GARCH model coefficients for the series SWAP5 and SWAP10 are presented in Tables 7 and 8 respectively. As it can be seen from the tables, self predictive power or ARIMA models is fairly low for both series.

A liquidity index is consider to be an estimate of changes in the difference between yields of the 10-year swap index and 10-year Treasuries, TRSW, as suggested by Collin-Dufresne, Goldstein and Martin (2001).The best ARIMA model is given in Table 7.

Table 7. ARMA-GARCH model coefficients for the series SWAP5

Dependent Variable: D(SWAP5)				
Included observations: 173				
	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.415908	0.263282	-1.579707	0.1142
MA(1)	0.58401	0.262362	2.225973	0.026
	Variance Equation			
C	0.090758	0.046474	1.952889	0.0508
ARCH(1)	-0.102324	0.04004	-2.555525	0.0106
GARCH(1)	0.152989	0.485436	0.315159	0.7526
R-squared	0.033673	Mean dependent var		-0.0217

Table 8. ARMA-GARCH model coefficients for the series SWAP10

Dependent Variable: D(SWAP10)				
Included observations: 173				
	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.69404	0.194109	-3.575512	0.0003
MA(1)	0.808037	0.1549	5.216516	0
	Variance Equation			
C	0.028355	0.054337	0.521849	0.6018
ARCH(1)	-0.036194	0.049834	-0.726295	0.4677
GARCH(1)	0.690456	0.645622	1.069443	0.2849
R-squared	0.01843	Mean dependent var		-0.0228

EUR/USD exchange rate was the only shorter time series used in this article. The missing values are obtained by using a weighted average of the foreign exchange value of the U.S. dollar against a subset of the G7 index currencies that circulate widely outside the country of issue, issued by the Board of Governors of the Federal Reserve System for the period 1991-1999.Its ARMA –GARCH model parameters are presented in Table 10.

It is not unusual that instead of EUR/USD exchange rate, researchers use TED spread, or treasury rate – EUR/USD exchange rate (Harvey 1999). Since the Credit Spread already contains treasury rate yields, we prefer to use the exchange rate itself.

Table 9. ARMA-GARCH model

Dependent	Variable:	D(TRSW)		
Method:	ML	ARCH	(Marquardt)	
Sample				
Included	observations:	172		
	Coefficient	Std.Error	z-Statistic	Prob.
AR(2)	0,7312	0,1241	5,8926	0,0000
MA(1)	-0,7426	0,0538	-13,7959	0,0000
MA(2)	-0,8315	0,0925	-8,9858	0,0000
MA(3)	0,6565	0,0893	7,3553	0,0000
	Variance	Equation		
C	0,0019	0,0003	6,7920	0,0000
ARCH(1)	-0,0776	0,0034	-22,8489	0,0000
GARCH(1)	1,0186	0,0089	115,0676	0,0000
R-squared	0,2884			

Table 10. ARMA –GARCH model parameters

Dependent Variable: D(EUR/US)				
Date: 03/09/14 Time: 12:00				
Included observations: 174 after adjusting endpoints				
	Coefficient	Std. Error	z-Statistic	Prob.
MA(1)	0,464845	0,088904	5,22861	0
MA(2)	0,004959	0,072703	0,068205	0,0094
	Variance Equation			
GARCH(1)	-0,128229	0,014563	-8,805107	0
	1,025287	0,017666	58,03805	0
R-squared	0,165566	Mean dependent var		-0,0009

The U.S. Leading index, as issued by the Conference Board, is a composite average of ten components: Average weekly hours (weight .189), Average weekly initial claims for unemployment insurance (.026), Manufacturers' new orders, consumer goods and materials (.049), Vendor performance, slower deliveries diffusion index (.027), Manufacturers' new orders, non-defense capital goods (.012), Building permits, new private housing units (.018), Stock prices, 500 common stocks (.033), Money supply, M2 (.306), Interest rate spread, 10-year Treasury bonds less federal funds income ratio (.323), Index of consumer expectations (.017). Dudukovic (2005) demonstrated the causality between the credit spread and the U.S. leading composite index returns and showed that leading index explained up to 30% of credit spread changes.

ARMA-GARCH model for USLEAD percent changes, USLEADR, is presented in Table 11.

Repo rate as explanatory variable are suggested by Lando (2002). It is well known that the market for repurchase agreements involving Treasury securities (known as the repo market) plays a central role in the Federal Reserve's implementation of monetary policy. Transactions involving repurchase agreements (known as repos and reverses) are used to manage the quantity of reserves in the banking system on a short term basis. By undertaking such transactions with primary dealers, the Federal Reserve Bank, through the actions of the open market desk, can temporarily increase or decrease bank reserves.

By definition, repo rate is the rate of return that can be obtained from selling a debt instrument future contract and simultaneously buying a bond or note deliverable against that future contract with borrowed funds.

The best ARIMA-GARCH model for those rates is given in Table 12.

Table 11. USLEADR

Dependent Variable: USLEADR100				
Included observations: 173				
	Coefficient	Std. Error	z-Statistic	Prob.
AR(2)	0.939386	0.034147	27.51011	0
MA(2)	-0.772158	0.077257	-9.994679	0
	Variance Equation			
C	0.356773	0.069682	5.120015	0
ARCH(1)	0.108312	0.051191	2.115844	0.0344
GARCH(1)	-0.814267	0.256766	-3.171236	0.0015
R-squared	-0.004185	Mean dependent var		0.0032

Table 12. The best ARIMA-GARCH model

Dependent Variable: D(REPO3)				
Included observations: 169 after adjusting endpoints				
	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.855709	0.077274	11.0737	0
MA(1)	-0.606855	0.112583	-5.390271	0
	Variance Equation			
C	0.019547	0.011925	1.639159	0.1012
ARCH(1)	-0.034796	0.002004	-17.36755	0
GARCH(1)	0.548244	0.282948	1.93761	0.0527
R-squared	0.225874	Mean dependent var		-0.0124

The Russell 2000 index measures the performance of the smallest 2000 companies in the Russell 3000. It is published by the Frank Russell Company. The index itself is considered to be the benchmark for all small-cap mutual funds. The best ARMA-GARCH model is presented in Table 13. *Default Rate.* We use Moody's monthly default rates for all corporate U.S. issuers (available on Bloomberg and, discontinued in 2002). A significant positive relationship between the credit spread and default rates is reported in by Huan and Hong, 2003, where the standard regression analysis is used to explain credit spread changes.The best ARIMA-GARCH for default Moody's default rates is presented in Table 14.

Table 13. Default Rate

Dependent Variable: R2000R				
Included observations: 173 after adjusting endpoints				
	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0,375244	0,278737	1,346228	0,1782
MA(1)	-0,267793	0,295763	-0,905432	0,3652
	Variance Equation			
C	5,52E-05	6,70E-05	0,824652	0,409
ARCH(1)	0,058571	0,056084	1,044343	0,0296
GARCH(1)	0,92554	0,067004	13,81327	0
R-squared	0,022226	Mean dependent va		0,0097

Table 14. Moody's default rates

Dependent Variable: D(MDEFAULTR)				
Included observations: 136				
	Coefficie	Std. Error	z-Statisti	Prob.
AR(1)	0,82976	0,087785	9,45222	0
MA(1)	-0,5206	0,141277	-3,6852	0,0002
	Variance Equation			
C	0,00042	0,000245	1,72445	0,0846
ARCH(1)	0,03117	0,035966	0,86661	0,3862
GARCH(1)	0,91387	0,049796	18,3525	0
R-squared	0,21959	Mean dependen		-0,0017

Dynamic model - empirical results

The proposed dynamic regression model , is tested by using E-Views software. Different model equations are used, with different lags for independent variables. The resulting model is chosen as one for which all the variables were statistically significant, according to t-values and p values.

According to Table 15, Credit Spread determinants are proven to be: U.S. leading index, Russell 2000 returns, interest rate SWAPS, S& P 500 returns, Treasury bill changes, liquidity index and Moody's default rates.

Table 15. Macro-Financial CRSP Model

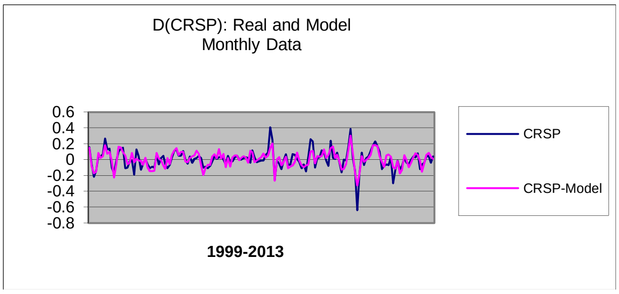
Dependent	Variable:	D(CRSP)		
Date: 03/09/14 Time: 12:00				
Included	observation	135		
Variable	Coefficient	Std.Error	t-Statistic	Prob.
USLEADR100(-1)	-0.04	0.01	-3.27	0.00
USLEADR100(-3)	0.03	0.01	3.03	0.00
D(SWAP5(-2))	0.04	0.02	1.89	0.12
D(SWAP10(-1))	-0.28	0.03	-9.27	0.00
D(TRE3M(-2))	-0.14	0.04	-3.95	0.00
D(CRSP(-1))	0.33	0.06	5.34	0.00
D(TRE3M(-1))	0.15	0.03	4.30	0.00
SP500R(-1)	0.21	0.12	1.72	0.11
R2000R(-1)	-0.28	0.11	-2.54	0.01
D(MDEFR(-1))	-0.08	0.04	-2.04	0.11
D(MDEFR(-2))	0.11	0.05	2.20	0.03
D(TRSW(-1))	-0.30	0.04	-7.61	0.00
	Variance Equation			
C	0.00	0.00	1.79	0.07
ARCH(1)	-0.06	0.07	-0.91	0.36
GARCH(1)	0.70	0.17	4.18	0.00
R-squared	0.729435	Mean dependent v		0.002

Surprisingly, the volatilities of S&P 500, the volatility of Credit Spread and the volatility of Treasury bills are neither significant for credit spread changes, nor for the change of R-squared. This could be seen from Table 16, which has to be read as the bottom part of Table 15. The same holds for Repo rates, LIBOR and US&EUR exchange rate .This contradicts Huang and Kong, 2003 and Lando 2005. The real Credit Spread and its IAR-GARCH model are presented in Figure 2.

Table 16.

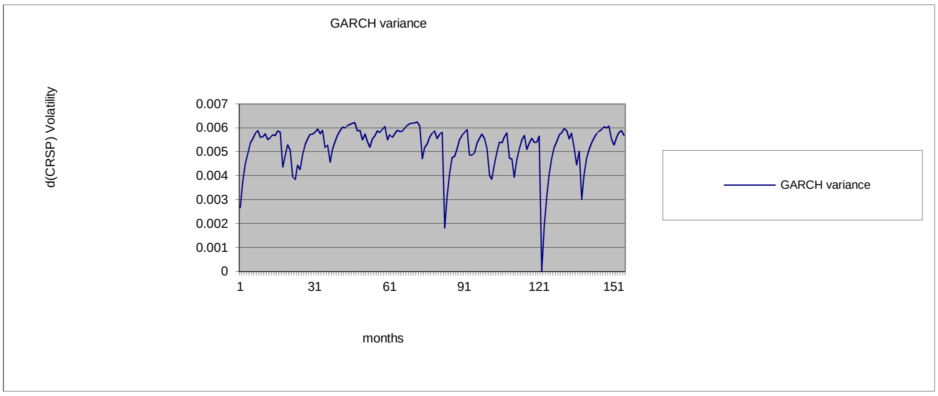
Dependent	Variable:	D(CRSP)		
Variable	Coefficient	Std.Error	t-Statistic	Prob.
CRSPVOL	0,667885	0,86558	0,771606	0,442
SPVOL	0,218875	5,63366	0,038851	0,969
TBILL3MVOL	-0,322887	0,30795	-1,04851	0,297
REPO3(-1)	0,001459	0,00684	0,213343	0,831

Figure 2. Real Credit Spread differences and its IAR-GRACH model.



The residual volatility obtained by using GARCH model is presented in Figure 3.

Figure 3. Credit Spread Volatility



HOC approach to Credit Spread Modeling

The new approach to the Credit Spread forecasting, suggested in this paper, is based on ARIMA- GARCH model (Engel -Boleslev1996). The model building, as usually, consists of three steps: model identification (order determination using Akaike's information criterion – AIC), parameter estimation and model testing. The main premises in this methodology is that each stationary time series is treated as the output of AR(p), MA(q) or ARIMA filter, which has as the input uncorrelated non Gaussian shocks known as "white noise" :A(Z)* DY_t= B2(Z)* v_t ,where v_t is a white non Gaussian noise , Z is a backward shift operator:

$Y_{t-1}=ZY_t$, $Y_{t-k}=Z^kY_t$, $A(Z) = 1-\alpha_1 Z-\alpha_2 Z^2 -\alpha_p Z^p$ and $B(Z) = 1-\beta_1 Z-\beta_2 Z^2 - \ldots\beta_q Z^q$ are AR and MA filters of orders p and q respectively, D is the first difference filter, $DY_t = Y_t - Y_{t-1}$, $D^kY_t=Y_t - Y_{t-k}$

As for volatility its model is given by Engle (1982) :

$$h_t=\alpha_0 + \sum_{i=1}^{p} \alpha_i r^2_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (4)$$

in which p_t represents stock prices, $\{r_t\}$ represent random returns, h_t is the conditional volatility, α_i is autoregressive, and β_j is the moving average parameter as related to the squared stock market index residuals.

An equivalent ARMA representation of the GARCH (p, q) model is given by:

$$e_t^2 = \alpha_0 + \sum_{i=1}^{P} (\alpha i+\beta_i)\, e^2_{t-i} + \nu_t - \sum_{j=1}^{q} \beta_j \nu_{t-j} \qquad (5)$$

where ·t = e_t^2 - h_t and, by definition, it has the characteristics of (i.i.d) white noise.

In other words, the GARCH (p, q) volatility model is an Autoregressive Moving Average (ARMA) model in et2 driven by white noise ·t .The rt2 Is stationary if (·i+ ·i)< 1

The aim of this paper is to take a new direction which leads back to the essence of Time Series Analysis. Namely, it is argued that the sufficient statistics for Credit Spread is defined in terms of the higher order cumulant (HOC) function. It is hypothesized that the hoc model extracts the information about the Credit Spread , better if ARMA parameters are calculated by using both second, third and fourth order cumulant functions.

A new method of parameter estimation for non Gaussian processes is based on the higher order cumulants. The third $C^3{}_y$ and the fourth order cumulants $C^4{}_y$ are defined by Gianninakis (1990):

$$C^3{}_y(\tau1,\tau2)= (\sum(y(t)y(t+\tau_1)y(t+\tau_2))/n,$$

$$C^4{}_y(\tau1,\tau2)= (\sum(y(t)y(t+\tau_1)y(t+\tau_2)\, y(t+\tau_3))/n,$$

Oyet A. (2000, pg 4) and Zou at all.(2013) proved that efficient ARMA parameters can be obtained by using a modified set of Yule Walker equations where autocorrelations are replaced by third or fourth order cumulants:

$$\sum_{1=1}^{p} \alpha i\, C^3(k-i,k-l) = -\ C^3(k,k-l) \quad , \quad k\geq l\geq q+1 \qquad (6)$$

$$\sum_{1=1}^{p} \alpha i\, C^4(k-i,k-l, k-m) = -\ C^4(k,k-l, k-m) \quad , \quad k\geq l\geq m\geq q+1 \qquad (7)$$

Swami (1989) developed the MATLAB routine AREST which enable AR parameter estimation using both the second and the third order cumulants .

Once the AR residuals are calculated, the MA parameters can be calculated by using the routine MAEST which uses the least squares set of equations:

$$\sum_{1}^{q}\beta_i\, C^3(n-i,n-i)-\sum_{1}^{q}\beta_i{}^2 C^2(n-i) =C^2(n)\ ,\ N= -q\ldots,2q \qquad (8)$$

where both second and third order cumulants are used.

With the above theory in mind, the higher order cumulants are used for Credit Spread ARIMA modeling. The forth order CRSP cumulants are presented in Figure 4.The different factors discussed here were investigated using MATLAB and its Higher-Order Spectral Analysis (HOSA) toolbox. MATLAB was used to calculate estimates of the data's third-order cumulants, as well as to estimate ARMA model parameters. Further residuals analysis is done using E-Views.

The obtained cumulants based model parameters are presented in Table 18. The model and the real Credit Spread data are presented in Figure 5.

Figure 4. Third order cumulants for Credit Spread first difference

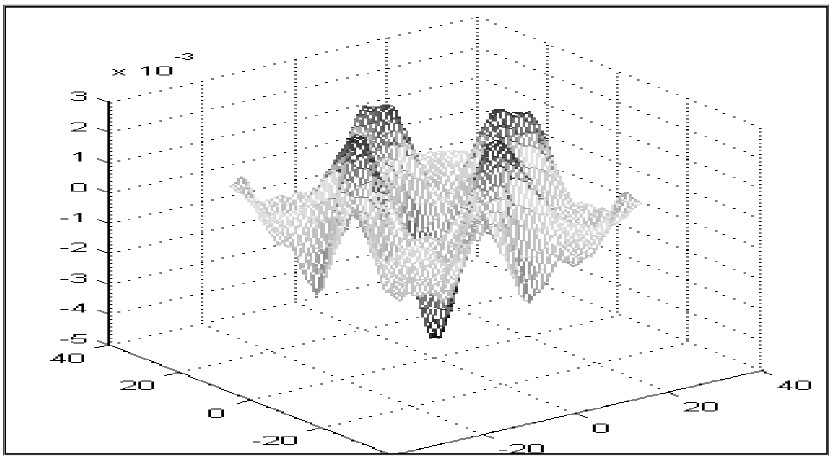


Figure 5. Cumulant based Credit Spread Model

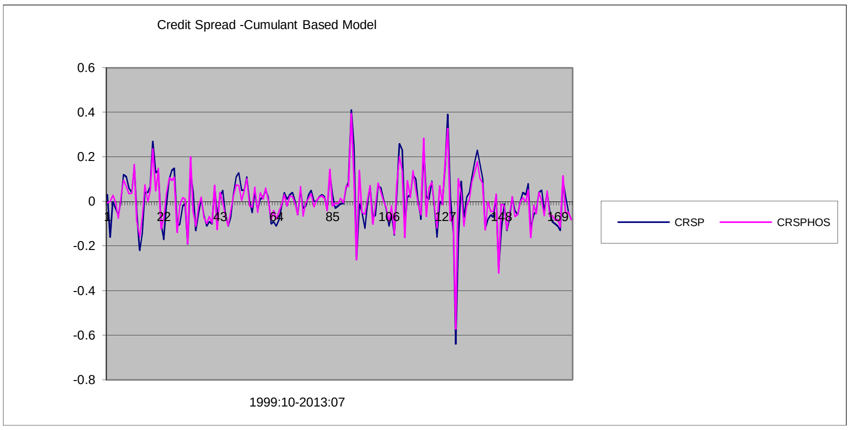


Table 18. Cumulant based ARIMA estimates

Dependent Variable: DCRSP				
Method: Cumulant Based Least Squares				
Date: 12/02/07 Time: 18:57				
Sample(adjusted): 4 174				
Included observations: 171 after adjusting endpoints				
Convergence achieved after 30 iterations				
Backcast: 1 3				
Variable	Coefficien	Std. Error	t-Statistic	Prob.
AR(1)	0,939886	0,152151	6,177341	0
AR(2)	0,668867	0,217999	3,068214	0,0025
AR(3)	-0,71802	0,114241	-6,28511	0
MA(1)	-0,1833	0,103085	-1,77816	0,2911
MA(2)	-0,35279	0,167842	-2,10191	0,0371
MA(3)	0,166202	0,08135	2,043051	0,1616
R-squared	0,857758	Mean dependent v		0,0075

Concluding remarks

The credit spread predictability, defined as the difference between AAA corporate bond yields and 10 year Treasury bond yields, has assumed a new importance since both investor managers as well as corporate finance managers need credit spread predictions to make more money.

The multiple lagged IAR-GARCH model for the U.S. Credit Spread is made in this paper for the period 199:01 to 2013:07. As explanatory macro-financial variables we investigated: U.S. leading index, Russell 2000 returns, interest rate SWAPS, S&P500 returns, Treasury bill changes, liquidity index and Moody's default rates, S&P 500 volatility, credit spread volatility, treasury bill volatility, exchange rates EUR/USD, Repo rates and Libor rates. All the volatilities, Repo rates, Libor rate and exchange rates were not found to be causally related to credit spread changes. However, Credit Spread determinants are proven to be the following macro variables:

U.S. Leading index, Russell 2000 returns, interest rate SWAPS, S& P 500 returns, Treasury bill changes, liquidity index and Moody's default rates.

The obtained macro model significantly improves predictability of credit spread changes. Structured models based on micro independent variables, default rate and recovery rate, have explanatory power which varies from 20% to 50%.The proposed model explains 73% of the credit spread variability.

The advantage of the lagged model over the classical instantaneous multiple regression models like (Huang and Kong, 2003) is that our model enables prediction, since the model relates future credit spread change and the current and past values of the explanatory variables or their changes.

The second part of the paper introduces the estimation method based on higher order cumulants.Namely, it is argued that the sufficient statistics for Credit Spread is defined in terms of the higher order cumulant (HOC) function. It is hypothesized that the hoc model extracts the information about the Credit Spread, better if ARMA parameters are calculated by using both second, third and fourth order cumulant functions.

A comparison with a dynamical regression model is also provided. Ultimately, it is demonstrated that much of the information about the variability of the Credit Spread can be extracted from higher order cumulants. In fact the coefficient of determination obtained by regression for Credit Spread data is .729 while the coefficient of determination obtained by using the third order cumulants and applying HOS method appears to be .857. This demonstrates the fact that the HOS based ARMA estimation achieves statistically higher coefficient of determination.

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Modeliranje Creditnog Spreda Macro-finansijskom metodom i metodom KVR

REZIME *– Cilj ovog rada je da objasni promene kreditnog spreda u zavisnosti od promena macro-finansijskih variabli koje nemaju Gausovsku raspodelu. Prvi deo rada predstavlja empirisku analizu baziranu na spredu između prinosa desetogodišnjih korporativnih AAA obveznica i državnih zapisa sa desetogodišnjim rokom dospeća (10yTB). Makrofinansijske variajable uključuju indekse kao što su vodeći indeks rasta (US leading index), stock market indeksi Russel 2000 i S&P500, S&P volatilitet, kurs EUR/USD, Repo interesna stope, promene cena BBB korporativnih obveznica, promena cena državnih ili trezorskih zapisa (Tbills), indeks likviditeta, referentna kamatna stopa LIBOR, Moody stopa otpisivanja, volatilitet kreditnog spreda i volatilitet trezorskih zapisa. Predloženi diniamicki regressioni model objasnjava 73% varianse kreditnog spreda u SAD-u. Drugi deo rada uvodi estimaciju parametara ARMA model kreditnog spreda, baziranu na kumulantima višeg reda - KVR. Demonstrirano je empiriski da uvedeni metod estimacije ekstrahuje 85% informacije o varijansi kreditnog spreada.*

KLJUČNE REČI*: modeliranje kreditnog spreda, Ocena ARMA parametara, kumulanti višeg reda, Ne-Gausivi ARMA modeli, dinamička regresija*

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