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CDS Industrial Sector Indices, credit and liquidity risk

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Abstract
This paper studies the risk spillover among US Industrial Sectors and focuses on the connection between credit and liquidity risks. The proposed methodology is based on quantile regressions and considers the movements of CDS Industrial Sector Indices depending on common risk factors such as equity risk, risk appetite, term spread and TED spread. We use CDS Industrial indexes and the market risk factor to identify the impact of market liquidity risk and market credit risk in the different US Industries and give evidence of the heterogeneity of this relation. We show that all the sectors are largely exposed to the non investment grade bond spread indicating that credit risk is largely a common factor rather than a sector specific factor. With a lower impact, we also find that market risk and interest rate risk are also common factors, as well as liquidity risk. These results indicate that diversification among sectors might collapse when credit, equity and liquidity events hit the market. The information extracted from CDS market could thus provide relevant information for sector allocation strategies.

Keywords
Credit Risk, Common factors, liquidity risk
JEL Codes
F34, G12, G15.

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1 Introduction

Is sector credit risk primarily an industry-specific type of risk? Or, is sector credit driven primarily by common factors? How stable is this relationship? Understanding the nature of credit risk industrial sectors is of key importance given the large and rapidly increasing size of the corporate bond and CDS markets. Furthermore, the nature of credit risk industrial sector directly affects the ability of financial market participants to diversify the risk of debt portfolios.

However, despite the importance of CDS in the financial markets, relatively little research about the sources of commonality of these financial products has appeared in the literature.

This paper investigates these issues using four different methodologies. We first perform a simple dynamic correlation analysis. Second, we use principal component analysis to estimate the number and importance of common factors driving the changes in the CDS indexes. Third, we consider the Exceedence Correlation (EC) of Longin and Solnik (2001) to investigate the heterogeneity of the exposures to different observable factors. Fourth, we perform a quantile regression to investigate the heterogeneity of the exposures among different states of the common factors. We use an extensive database of Credit Derivatives Swap of US Industrial Sector Indices.

A Credit Derivatives Swap (CDS) contract is similar to an insurance contract: it obliges the seller of the CDS to compensate the buyer in the event of loan default. It is a swap because generally, the agreement is that in the event of default the buyer of the CDS receives money (usually the face value of the bond), and the seller of the CDS receives the defaulted bond. This contract therefore is able to measure precisely the credit risk embedded in a corporate bond.

We consider as observable factors ten different financial variables that are able to capture common exposure to (i) market risk, (ii) credit risk, (iii) liquidity risk and (iv) interest rate risk.

Three important results emerge from the analysis. First, the simple correlation analysis highlights that CDS industrial sector indexes co-move but with different intensity through time. Second, the co-movements are largely characterized by the common exposure to a single risk factor, that explain on average 82% of the changes of the 18-CDS indexes. However, this exposure changes a lot through time (from 33% till 96%) indicating that the relationship is not stable and not linear. Third, the exposure to credit risk and interest rate risk is non linear, and is larger when already the high yield bond stread and interest rates faces large cahnges. This means that there are some amplifying mechanisms in the transmission of credit and interest rate risks. These results indicate that diversification among sectors might collapse when credit and liquidity events hit the market. The information extracted from CDS market could thus provide relevant information for sector allocation strategies.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents the different approaches used to investigate the linearity of the relation across CDS and its stability and the results. Section 5 concludes.

2 The data

The data for the five-year CDS of US Industrial indexes used in this study are obtained from Datastream and are based on CDS market quotation data from industry sources. The sample covers the period from January 2004 untill December 2011.

We have considered the CDS Indexes of 18 sectors: Automobile (AUTOMOB), Banking (BANKING), Basic Resouces (BASICRES), Chemical (CHEMIC), Construction and materials (CONSTMAT), Financial services (FINSERV), Food and beverage (FOODBEV), Health care (HEALTCARE), Industrial goods and Services (INDLGDS), Insurance (INSURAN), Media (MEDIASEC), Oil and Gas (OILEGAS), Personal and Household Goods (PSNLHSLD), Retails (RETAILSEC), Technology (TECHNOL), Telecomunication (TELECOM), Travel and Leisure (TRAVLEI) and Utilities (UTILITIES). The beginning of this sample period is dictated by the availability of liquid CDS data.

Table 1 provides summary information for the daily CDS Indexes. All CDS Indexes are denominated in basis points and are, therefore, free of units of account for the CDS swap contracts. The average values of the CDS range widely across indutries. The lowest average is 94.93 basis points for Banking; the highest average is 758 basis points for Automobile sector. Both the standard deviations and the minimum/maximum values indicate that there are significant time-series variation in sovereign CDS premiums.

Table 1 also reports the summary statistics of the daily changes in sovereign CDS premiums. In Figure 1, we report the dynamic of the changes in the CDS spreads through time.

Table 2, to provides additional descriptive statistics, reports the correlation matrix of daily changes in the five-year CDS Index spreads. Table 2 shows that, while there is clearly significant cross-sectional correlation in spreads, the correlations are far from perfect. Most of the correlations are less than 0.7, and a few are negative. The average correlation across the 18 sectors is 0.25.

Since there is virtually an unlimited number of variables that could be related to Industry credit risk, it is important to be selective in the variables considered. We use the daily return on the NYSE index (log-return) and the daily change in the VIX volatility index from the financial stock market.

From the bond market, we use the changes in the spreads of U.S. investment-grade and high-yield corporate bonds. Specifically, we include the change in the spreads between five-year BBB- and AAA-rated bonds and between five-year BB and BBB-rated bonds. The former captures the range of variation in investment-grade bond yields, while the latter reflects the variation in the spreads of high-yield bonds.

From the government bond market, we use "term spread" calculated as the difference between the yield to maturity of the 10-year Treasury bond and the 13-week Tbill rate.

Moreover, recent research on corporate credit spreads suggests that these spreads may include premiums for bearing risks such as jump-to-default risk, recovery risk, the risk of variation in spreads or distress risk, liquidity risk, etc. As a proxy for the variation in the equity risk premium, we use monthly changes in the earnings-price ratio for the S&P 100 index. As another risk premium proxy, we use monthly changes in the spreads between implied and realized volatility for index options. We use monthly changes in the expected excess returns of five-year Treasury bonds as a proxy for changes in the term premium.

Liquidity risk is captured using two variables: the change in the difference between the US repo rate and the 13-week Tbill rate, and the change in the difference between Libor and the 13-week Tbill rate.

Table 3 provides summary statistics of these 10 variables.

Table 4 reports the correlations between the changes in the CDS Indexes and the conditioning variables. As the Table shows, the correlations of the different CDS indexes and the common factors are quite different; however, the sign of the correlations are almost the same for all the different sectors.

3 Methodology and Results

3.1 Preliminary analysis

As a first evaluation of the linearity of the relation across CDS and its stability we consider the rolling evaluation of the linear correlation. We calculate correlation among changes in CDS spreads considering 60 observations, roughly equivalent to one quarter. The rolling correlation (average across the 18 sectors correlations) is plotted in Figure 2 from March 2004 through January 2011. This figure shows overall high values of the correlation between changes in the

CDS Indexes (generally between 0.13 and 0.88). Furthermore, we observe that the correlations across the Industries changes largely through the sample. Starting from December 2008, it has increased from 0.30 to 0.80. Looking to the last part of the sample it seems that the averall correlation among the different countries has been reduces. However, this is not the case for all the Industries. For example, in the last part of the sample the correlation with Utilities and almost all the other Industries has increases[1].

Increased commonality among CDS Sector Indexes can be empirically detected by using principal components analysis (PCA), a technique in which the changes of the CDS Indexes are decomposed into orthogonal factors of decreasing explanatory power (see Muirhead, 1982 for an exposition of PCA).

The time-series results for the Cumulative Risk Fraction (i.e., eigenvalues) are presented in Figure 3. The time-series graph of eigenvalues for the most important principal components (PC1, PC2, PC3, and PC4) shows that the first principal component captures the majority of changes in CDS during the whole sample, but the relative importance of these groupings varies considerably. The time periods when the first principal components explain a larger percentage of total variation are associated largely with the last part of the sample. In particular, Figure 3 shows that the first principal component is very dynamic, captures from 33% to 99% of CDS variation, increasing significantly during crisis periods. The PC1 eigenvalue increases from the beginning of the sample, peaking at 96% in 2004, and subsequently decrease. The PC1 eigenvalue starts to increase in 2005 during the GM/Ford crisis, declines slightly in 2006, and increases again in 2007 and subsequently decrease. In 2009 it continues to increase in line with the Sovereign European crisis. As a result, the first principal component explaines 82% of CDS variation over the 2010-2011. The results show that there is strong commonality in the behavior of CDS Industrial Indexes.

As a further analysis, we consider the exceedence correlation (EC) of Longin and Solnik (2001). EC is a conditional correlation measure across two time series. It takes into account only those observation when the two time series are both above (below) a given empirical quantile. In formulae, if we consider the quantile or order α, and focus on two economic sectors i and j, EC is computed as follow:

$$EC^{-} = Corr\left[\Delta CDS_{i,t}, \Delta CDS_{j,t} | F_i\left(\Delta CDS_{i,t}\right) < q, F_j\left(\Delta CDS_{j,t}\right) < q\right], \tag{1}$$

$$EC^{+} = Corr\left[\Delta CDS_{i,t}, \Delta CDS_{j,t} | F_i\left(\Delta CDS_{i,t}\right) > 1-q, F_j\left(\Delta CDS_{j,t}\right) > 1-q\right]. \tag{2}$$

where F_i and F_j are the cumulative density functions of the corresponding CDS variations.

[1] The rolling window correlations among the sector indices are available upon request

Therefore, EC is given by two values, EC^- measures the correlation in the lower quantiles α, while EC^+ considers observations above $1-\alpha$. EC is generally measured for several values of α. By convention, the graphs report at the center (for $\alpha = 0.5$) the full sample standard correlation, while on the two sides we have EC^- (on the left) and EC^+ (on the right).

Table 6 presents the summary statistics of the exceedence we have calcualted among the different sectors. We report the exceedence correlations by reporting in the middle the full sample standard correlation while on the left and right sides we report ρ^- and ρ^+, respectively. As the mean, the min, the maximum and the different percentiles shows, in most cases the exceedence correlation ρ^+ is decreasing as q decreases (note that ρ^+ considers the correlation above the quantile $1-q$), suggesting that large positive CDS changes correspond to lower the correlation across sectors. The same for the opposite: for large negative CDS changes, the correlation across sectors tends to decrease (in most cases). This result seems to indicate that the relation the relation across CDS sectors is not linear: is is higher when there are small positive or negative changes but for large changes in the cds of one sector the relationship is quite low and in some cases is also negative.

3.2 Common factor analysis

3.2.1 Covariates impact at Exceedence

The relation between the covariates and each economic sector is evaluated using again the Exceedence measure and the Quantile Regressions.

Regarding the Exceedence measure we have considered the conditional correlation measure across the CDS Sector $\Delta CDS_{i,t}$ and the covariate variable $\Delta X_{j,t}$.

In formulae, if we consider the quantile or order α, EC is computed as follow:

$$EC^- = Corr\left[\Delta CDS_{i,t}, \Delta X_{j,t} | F_i\left(\Delta CDS_{i,t}\right) < q, F_j\left(\Delta X_{j,t}\right) < q\right], \tag{3}$$

$$EC^+ = Corr\left[\Delta CDS_{i,t}, \Delta X_{j,t} | F_i\left(\Delta CDS_{i,t}\right) > 1-q, F_j\left(\Delta X_{j,t}\right) > 1-q\right]. \tag{4}$$

where F_i and F_j are the cumulative density functions of the corresponding CDS and X variations.

Table 7 presents the average of the exceedence we have calcualted among the different sectors. As the Table shows, in most cases the exceedence correlation ρ^+ is decreasing as q decreases, the same for the opposite: for large negative CDS changes, the correlation among sectors and covariates tends to decrease, suggesting again that large positive or negative CDS changes correspond to lower the exposures to covariates. This result confirms those obtained in the previous section: the relation across CDS sectors is not linear and it seems largely driven by common factors that are relevant in normal times but not when there are turbolence in the market. In fact, the linkages are rather large and the first principal component is able to explain more than 80% of the variability of all the sectors when the market is in normal time. During the other periods we have that the linkages are rather low (some times negative) and the fist principal component is able to explain only 35% of the variability of all the sectors. This pattern is well represented by figure 4.

3.2.2 Covariates impact at quantiles

The analysis performed above concentrates on pairwise relationship. Quantile regression offers a systematic strategy for examining how variables influence the location, scale, and shape of the entire response distribution. The advantage is that quantile regressions is a particularly efficient way to estimate a linear relation that vary across quantiles. This is an extremely flexible way to detect the presence of relation asymmetries in the data.

We group the covariates in the vector X_t and we are interested in monitoring the contemporaneous impact of changes in X_t on the changes in the sector CDS. The Quantile Regression coefficients are estimated by solving the following minimization problem

$$min_{\beta_0,\beta_1} \sum_{t=1}^{T} \rho_\alpha \left(\Delta CDS_{i,t} - \beta_0 - \beta_1' X_t\right) \tag{5}$$

where $\rho_\tau\left(a\right)$ is the *check* function for quantile α defined as $\rho_\alpha\left(X\right) = X \times \left(\alpha - I\left(X < 0\right)\right)$ and β_1 is the vector of coefficients linking the covariates to the sector CDS index. Given the estimated coefficients, the α quantile for $\Delta CDS_{i,t}$ is given as

$$Q_t\left(\alpha\right) = \widehat{\beta}_{\alpha,0} + \widehat{\beta}'_{\alpha,1} X_t \tag{6}$$

where the hat denotes estimated values while the α highlights that the estimated coefficients are quantile-specific. To evaluate the coefficients standard errors we resort to the bootstrap-based procedure of Kocherginsky et al. (2005). Such a choice robustify the results with respect to the possible presence of heteroskedasticity. The readers interested on further details on quantile regression should refer to Koenker (2005).

The impact of covariates clearly depends on the chosen quantile level α. In order to evaluate the changes in the correlation between covariates and sector CDS indices across different quantiles, we estimate the model in (5) for the following quantile levels: 0.01, 0.015, 0.02, 0.025, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95, 0.975, 0.98, 0.985, 0.99. The estimated coefficients can be graphically represented together with the corresponding standard errors in order to evaluate the stability of the relation at different quantiles.

Table 8 reports the estimated coefficients and the t-statistic for all the 18 sectors of the ten covariates respectively for the 0.05, 0.50 and 0.95 quantiles. Figure 6 shows the number of significant coefficients for each covariate. Table 8 and Figure 6 show that the covariate that is highly significant for all the quintiles is the the spreads of high-yield bonds portfolio. This variable is significant for all the sectors for the 0.95 and 0.50 quantiles and for 17 sectors for the 0.05 quantiles. This means that the most important common factor is the spread of the high-yield bonds portofolio, i.e credit risk. Table 8 shows that this factor has the same sign of impact across quantiles. This result indicates that the credit risk of all the sectors is largely driven by a common factor that characterizes the probability of default of all the sectors. The spread of the investment grade portfolio is instead significant for only three sectors and only for the 0.50 quantile. There is only another factor that is significant for all the different sectors, but only in the 0.50 percentile: the change in the NYSE. Therefore, the equity market is negatively affecting the different sector CDSs: an increase in the NYSE reduces the probability of default of the different firms and therefore the CDS reduces. This second common factor indicates that when there is a reduction in the equity market the credit risk (and therefore the probability of default) of all the different sectors is larger.

A factor that is common for 16 out of 18 sectors for the 0.95 quantile and for 15 out of 18 for the 0.50 quantile is the 5 year Treasury Bond rate. The coefficient is positive for all the sectors. This factor is largely related to the business cycle, i.e. when the Treasury Bond rate is high, the economy is in a booming state and the probability of default of all the sectors is lower.

The three variables that are in different ways related to liquidity risk: VIX, TED spread, Repo-Tbill rate. Among the three the one that is mostly relevant is the TED spread with a significant impact in different ways when the CDS are increasing and when CDS are decreasing over lower and hight quantiles. An increase of the TED spread turn to a further increase fo the CDS low quantile and a reduction on CDS high quantile. This result could be explained by the fact that when the TED spread is increasing also credit risk is increasing and therefore the two phenomena should be read together.

The other common factors are significant for a number of sectors that ranges from zero to 11. More specifically, P/E is not relevant, an increase in the risk appetite leads to a lower CDS change and is significant only for half of the sectors.

The term spread impact in different ways when the CDS are increasing and when CDS are decreasing over lower quantiles (CDS decreasing): increase in TS turns to a further decrease of

CDS (the quantile) over upper quantiles increase in Term Spread provides a further increase of CDS quantile.

4 Stability of relations

Beside the graphical comparison, some tests might be taken into account to verify the stability of the covariates impact on the CDS indices.

We take into account two tests. At first, we consider the equality of coefficients across the highest quantiles and verify the following null hypothesis: $H_0 : \widehat{\beta}_{0.90,1} = \widehat{\beta}_{0.95,1} = \widehat{\beta}_{0.99,1}$ and $H_0 : \widehat{\beta}_{0.95,1} = \widehat{\beta}_{0.98,1} = \widehat{\beta}_{0.985,1} = \widehat{\beta}_{0.99,1}$. The test has been proposed by Koenker and Basset (1982), and is a Wald-type test. Under the null, the test statistic follows a Chi-square distribution, where the degrees of freedom depend on the number of covariates entering the equation. When the covariates are K, the degrees of freedom are $2K$ in the first test, and $3K$ in the second case.

Table 9 shows that the null hypothesis of no differences among quantile exposures is rejected in most of the cases. Therefore, this analysis shows that the exposure to common factors are largely different when CDS presents positive or negative changes or when changes are large or small.

We also proceed to verify the stability of coefficients across time. For this purpose we create a step dummy, D_t which assumes value 1 after date m (and zero before). Then, we estimate the following quantile regression:

$$min_{\beta_0,\beta_1} \sum_{t=1}^{T} \rho_\alpha \left(\Delta CDS_{i,t} - \beta_0 - \beta_1' X_t - \delta' X_t D_t \right) \tag{7}$$

To null of stability of coefficients in the two subsamples 1 to m and $m+1$ to T is equivalent to $H_0 : \delta = 0$ and corresponds to a standard test for linear restrictions in the quantile regression framework (again a Wald-type test).

We have comsidered two subsamples: 2007-2011 and 2009-2011. In all the cases (i.e. 2004-2001 vs 2007-2011, 2004-2001 vs 2009-2011, 2007-2001 vs 2009-2011) we find that the null hypothesis of stability of the parameters has been rejected. This confirms the results of the different appraoaches we have used: the relationship between CDS indexes and common risk factors are largely unstable through time and heterogeneous among quantiles.

5 Conclusions

We study the nature of sectors credit risk using credit default swap data for 18 Industrial Sectors. We show that credit risk tends to be much more correlated across countries than are equity index returns for the same countries. Our results suggest that the source of these higher correlations is the dependence of sector credit spreads on a common set of global market factors, risk premiums, and liquidity patterns. Specifically, we find that the Sector CDS spreads are driven primarily by high-yield factors and the Treasury 5 year Bond rate. However, this relation is not linear and is not stable trough time. Nevertheless, there is strong evidence that in most of the sample considered common factors are able to explain most of the changes of CDS Industrial Sector Indices.

References

Duffie, Darrell. 1999. "Credit Swap Valuation." Financial Analysts Journal, 55(1):

73-87.

Eichengreen, B., and A. Mody (2000), "What Explains Changing Spreads on Emerging-Market Debt?", in (Sebastian Edwards, ed.) The Economics of International Capital Flows, University of Chicago Press, Chicago, IL.

Kamin, S., and K. von Kleist (1999), "The Evolution and Determinants of Emerging Market Credit Spreads in the 1990s", Working paper No. 68, Bank for International Settlements.

Koenker, Roger and G. Bassett, Jr. (1982). Robust Tests for Heteroskedasticity Based on Regression Quantiles, *Econometrica*, 50(1), 43-62.

Koenker, R. (2005), "Quantile Regression", Econometric Society Monographs, n. 38, Cambridge University Press, New York.

Koenker, R., and Q. Zhao (1996), "Conditional quantile estimation and inference for ARCH models", *Econometric Theory*, 12, 793-813.

Longin, F.M. and B. Solnik (2001), "Extreme correlation of international equity markets," *Journal of Finance* 56, 649–676.

Mauro, P., N. Sussman, and Y. Yafeh (2002), "Emerging Market Spreads: Then Versus Now", *Quarterly Journal of Economics* 117, 695-733.

Muirhead, R. J., (1982), Aspects of Multivariate Statistical Theory. John Wiley & Sons, New York.

Figure 1: CDS levels across the economic sectors

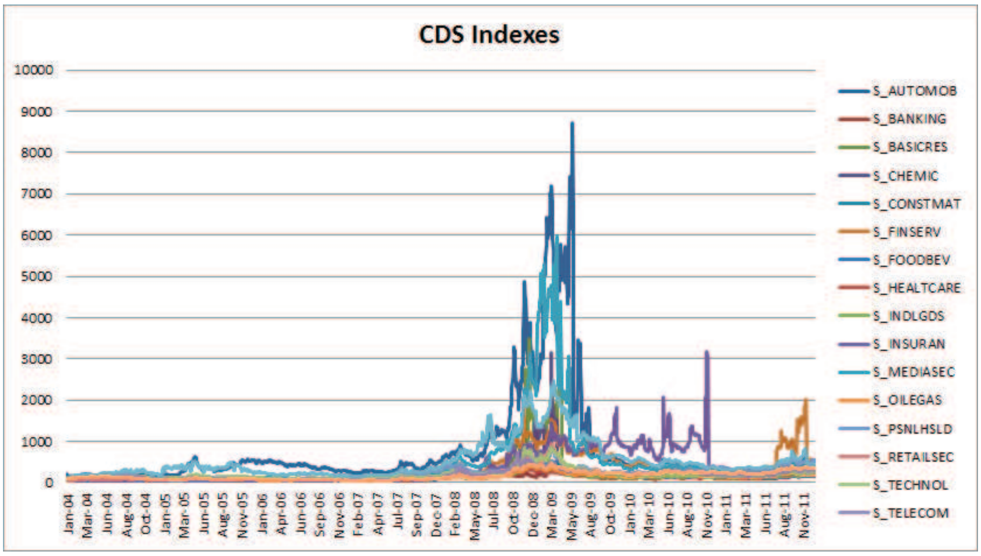

Table 1: **Summary Statistics**

Sector CDS levels					
	Mean	Standard Deviation	Minimum	Maximum	Median
AUTOMOB	758.84	1160.16	139.7	8717.72	420.31
BANKING	94.93	85.34	10.2	595.99	94.3
BASICRES	232.66	362.56	44.14	4066.7	137.98
CHEMIC	156.94	221.83	44.88	3155.08	104.99
CONSTMAT	178.28	120.13	31.72	610.51	155.74
FINSERV	306.72	355.13	21.36	2015.21	199.03
FOODBEV	108.69	70.51	29.38	394.57	93.15
HEALTCARE	108.09	58.6	34.2	322.43	107.03
INDLGDS	126.52	91.83	48.55	754.15	103.33
INSURAN	345.88	401.54	17.24	3182.45	141.44
MEDIASEC	465.31	826.82	56	5981.22	225.7
OILEGAS	128.44	76.01	42.98	406.42	107.56
PSNLHSLD	222.49	153.28	46.51	926.71	225.44
RETAILSEC	184.67	135.82	41.61	949.58	157.43
TECHNOL	200.39	132.46	70.95	863.13	163.6
TELECOM	182.9	109.56	47.96	707.32	176.5
TRAVLEI	521.69	433.76	96.32	2458.63	369.01
UTILITIES	169.48	102.11	38.62	452.15	134.48
Change in Sector CDS levels					
	Mean	Standard Deviation	Minimum	Maximum	Median
AUTOMOB	0.15	176.36	-5000.98	2568.11	-0.07
BANKING	0.1	11.64	-283.17	187.35	-0.02
BASICRES	0.11	99.67	-1722.25	1877.41	0
CHEMIC	0.03	60.53	-1076.7	1828.61	-0.03
CONSTMAT	0.13	5.83	-29.1	67.54	-0.02
FINSERV	0.24	46.02	-1361.87	754.63	-0.04
FOODBEV	0.05	3.13	-25.95	47.79	-0.02
HEALTCARE	0.06	2.78	-18.68	35.39	-0.04
INDLGDS	0.06	9.91	-314.88	230.78	-0.06
INSURAN	0.14	81.23	-2752.8	1191.93	-0.01
MEDIASEC	0.12	122.85	-2553.91	1857.08	0.01
OILEGAS	0.06	4.39	-54.66	57.61	-0.05
PSNLHSLD	0.23	10.44	-78.15	190.74	-0.01
RETAILSEC	0.12	7.56	-82.49	112.66	-0.05
TECHNOL	0.08	9.42	-111.02	92.14	-0.09
TELECOM	0.1	8.15	-132.1	175.33	-0.07
TRAVLEI	0.16	36.83	-650.47	338.76	-0.31
UTILITIES	0.12	4.65	-24.29	36.58	-0.06

Notes: This table presents summary statistics for daily 5 years CDS spreads and daily changes in CDS spreads for the 18 industrial sectors. The sample period considered is January 2004 to December 2011

Table 2: **Correlations**

Correlation Matrix																		
	AUTOMOB	BANKING	BASICRES	CHEMIC	CONSTMAT	FINSERV	FOODBEV	HEALTCARE	INDLGDS	INSURAN	MEDIASEC	OILEGAS	PSNLHSLD	RETAILSEC	TECHNOL	TELECOM	TRAVLEI	UTILITIES
	1																	
BANKING	0.11	1																
BASICRES	0.00	0.04	1															
CHEMIC	0.030	0.05	0.02	1														
CONSTMAT	0.23	0.30	0.06	0.06	1													
FINSERV	0.09	0.11	0.07	0.01	0.28	1												
FOODBEV	0.17	0.26	0.07	0.06	0.66	0.22	1											
HEALTCARE	0.18	0.28	0.05	0.09	0.69	0.2	0.72	1										
INDLGDS	0.07	0.14	0.01	0.04	0.28	0.12	0.28	0.29	1									
INSURAN	0.05	0.07	0.00	0.02	0.13	0.07	0.09	0.1	0.04	1								
MEDIASEC	0.08	0.01	-0.13	0.19	0.09	0.03	0.08	0.09	0.06	0.01	1							
OILEGAS	0.17	0.26	0.06	0.06	0.65	0.22	0.63	0.63	0.26	0.1	0.07	1						
PSNLHSLD	0.24	0.29	0.11	0.18	0.58	0.24	0.53	0.52	0.21	0.1	0.11	0.49	1					
RETAILSEC	0.33	0.28	0.05	0.11	0.66	0.23	0.63	0.61	0.22	0.11	0.16	0.53	0.65	1				
TECHNOL	0.23	0.25	0.09	0.06	0.57	0.23	0.51	0.53	0.21	0.09	0.11	0.48	0.46	0.53	1			
TELECOM	0.17	0.27	0.04	0.07	0.59	0.2	0.6	0.63	0.26	0.1	0.07	0.53	0.51	0.53	0.48	1		
TRAVLEI	0.1	0.13	-0.02	0.02	0.31	0.24	0.3	0.27	0.1	0.07	0.11	0.27	0.23	0.32	0.3	0.24	1	
UTILITIES	0.21	0.28	0.08	0.08	0.68	0.25	0.65	0.68	0.28	0.11	0.09	0.7	0.53	0.57	0.53	0.58	0.27	1

Notes: This table reports the correlation matrix of daily CDS index changes. The sample consists of daily observations for January 2004 to December 2011.

Table 3: **Summary Statistics of conditioning variables**

Conditioning variables levels					
	Mean	St.Dev.	Min	Max	Median
BB-BBB	1.78	0.99	0.52	6.37	1.47
BBB-AAA	1.49	0.9	0.5	4.73	1.41
LIQRISK	0.21	0.19	-0.1	1.72	0.15
NYSE	7649.92	1220.64	4226.31	10311.6	7484.5
RISK-APP	3.14	4	-23.76	26.18	2.92
SP100-PE	19.94	5.5	12.57	40.57	18.5
TBOND5RATE	3.14	1.2	0.79	5.23	3.18
TED	0.51	1.55	-2.04	5.14	0.68
TS	1.89	1.33	-0.62	3.85	2.17
VIX	21.16	10.69	9.89	80.86	18
Changes in conditioning variables					
	Mean	St.Dev.	Min	Max	Median
BB-BBB	0.00	0.07	-0.57	0.6	0
BBB-AAA	0.00	0.06	-1.52	1.53	0
LIQRISK	0.00	0.07	-0.94	0.58	0
NYSE	0.5	99.52	-686.36	696.83	4.13
RISK-APP	0.00	2.5	-26.43	18.67	0.06
SP100-PE	-0.01	0.49	-10.31	4.55	0
TBOND5RATE	0.00	0.07	-0.46	0.34	0
TED	0.00	0.07	-0.75	0.82	0
TS	0.00	0.08	-0.49	0.73	0
VIX	0.00	1.96	-17.36	16.54	-0.07

Notes: This table presents summary statistics for the conditioning variables. The sample period considered is January 2004 to December 2011

Table 4: **Correlations between conditioning variables and Sector CDS**

	BB-BBB	BBB-AAA	LIQRISK	NYSE	RISK-APP	SP100-PE	TBOND5RATE	TED	TS	VIX
AUTOMOB	0.16	0	0.03	-0.1	0.06	0	-0.08	0.03	-0.05	0.07
BANKING	0.21	-0.03	0.05	-0.24	0.18	-0.01	-0.11	0.06	-0.06	0.2
BASICRES	0.07	0	0	-0.05	0.01	0.05	-0.05	0	-0.02	0.01
CHEMIC	0.05	-0.04	0.05	-0.02	-0.01	-0.01	-0.04	0.03	-0.01	0.02
CONSTMAT	0.55	0.06	0.08	-0.44	0.3	-0.02	-0.26	0.11	-0.13	0.42
FINSERV	0.23	-0.04	0.04	-0.16	0.13	0.01	-0.12	0.06	-0.07	0.15
FOODBEV	0.47	0.08	0.07	-0.36	0.19	-0.02	-0.21	0.1	-0.08	0.31
HEALTCARE	0.52	0.07	0.06	-0.34	0.22	-0.04	-0.22	0.12	-0.08	0.31
INDLGDS	0.21	0.05	0.03	-0.12	0.08	0.02	-0.11	0.03	-0.06	0.09
INSURAN	0.11	-0.01	0.03	-0.1	0.1	0.08	-0.05	0.03	-0.02	0.11
MEDIASEC	0.07	-0.02	0.02	0.01	0	-0.03	-0.03	0.02	0	0.01
OILEGAS	0.48	0.09	0.02	-0.32	0.17	0.01	-0.19	0.07	-0.11	0.28
PSNLHSLD	0.41	-0.02	0.05	-0.34	0.22	-0.03	-0.18	0.07	-0.09	0.29
RETAILSEC	0.5	0.01	0.08	-0.37	0.28	-0.05	-0.25	0.09	-0.1	0.33
TECHNOL	0.4	0.02	0.08	-0.26	0.19	-0.04	-0.16	0.11	-0.02	0.25
TELECOM	0.45	0	0.06	-0.31	0.25	-0.05	-0.18	0.11	-0.06	0.33
TRAVLEI	0.23	0	-0.01	-0.12	0.09	-0.02	-0.06	0.02	-0.03	0.13
UTILITIES	0.51	0.07	0.07	-0.36	0.22	-0.01	-0.22	0.14	-0.08	0.31

Notes: This table presents the correlations between the changes in the conditioning variables and the changes in the Sector CDS. The sample period considered is January 2004 to December 2011

Table 5: **Coefficients of the covariates at different quantiles**

Covariates	Quantile	AUTOMOB	BANKING	BASICRES	CHEMIC	CONSTMAT	FINSERV	FOODBEV	HEALTCARE	INDLGDS	INSURAN	MEDIASEC	OILEGAS	PSNLHSLD	RETAILSEC	TECHNOL	TELECOM	TRAVLEI	UTILITIES
BB-BBB	0.05	1.86	0.21	—	0.26	0.39	0.93	0.22	0.23	0.29	0.99	1.04	0.31	0.56	0.46	0.48	0.58	1.62	0.34
	0.50	1.55	0.18	0.26	0.25	0.38	0.48	0.17	0.18	0.31	0.42	0.57	0.28	0.48	0.42	0.49	0.52	1.01	0.31
	0.95	3.78	0.27	0.41	0.30	0.49	1.42	0.23	0.26	0.38	1.02	1.36	0.35	0.73	0.62	0.65	0.61	1.53	0.41
BBB-AAA	0.05	—	—	—	—	—	—	—	—	—	—	0.60	—	—	—	—	—	—	—
	0.50	1.29	—	0.18	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.95	—	—	—	—	—	—	—	—	—	—	0.24	—	—	—	—	—	—	—
TS	0.05	-4.33	—	-0.73	-0.34	-0.21	-1.51	-0.11	—	—	-1.63	-1.27	—	—	—	—	—	—	—
	0.50	0.40	—	—	0.06	—	—	0.05	0.05	0.02	—	—	—	—	—	—	—	—	—
	0.95	5.78	—	1.23	0.73	—	—	0.23	—	—	—	2.03	0.18	0.57	0.62	0.68	0.14	1.76	—
LIQRISK	0.05	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	-0.10
	0.50	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.95	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
RISK-APP	0.05	—	0.01	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.50	—	—	0.00	—	0.00	—	0.00	0.00	—	—	—	0.00	—	—	—	—	—	0.00
	0.95	—	—	-0.02	-0.01	—	-0.02	-0.01	0.00	—	—	-0.04	-0.01	—	—	—	—	—	-0.01
TED	0.05	5.06	0.44	0.87	0.45	—	1.77	0.16	—	0.31	—	1.27	—	—	—	0.33	—	—	0.28
	0.50	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.95	-7.00	—	-1.49	-0.74	—	—	-0.28	—	-0.28	—	-2.62	-0.21	-0.60	-0.68	-0.70	—	-2.36	—
NYSE	0.05	—	-0.03	—	—	—	—	—	—	—	-0.05	—	-0.01	-0.02	—	-0.02	—	—	-0.01
	0.50	-0.04	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01
	0.95	—	-0.03	—	-0.02	-0.01	—	—	—	—	—	—	—	-0.02	—	-0.02	-0.01	—	—
TBOND5RATE	0.05	4.10	—	0.76	0.40	0.34	1.58	0.22	0.10	0.31	1.79	1.18	0.24	0.41	0.41	0.40	0.57	—	0.27
	0.50	0.30	—	0.10	0.05	0.14	0.17	—	—	0.11	0.15	0.20	0.11	0.17	0.14	0.13	0.24	0.40	0.09
	0.95	—	-0.30	-0.95	-0.52	—	—	-0.15	—	—	—	-1.32	—	—	-0.40	—	—	—	—
VIX	0.05	—	-0.01	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.00
	0.50	—	—	0.00	—	—	—	—	0.00	—	0.01	—	0.00	—	0.00	—	0.00	—	0.00
	0.95	—	—	—	—	0.01	—	0.01	0.00	—	—	—	0.01	—	—	—	—	—	0.01
SP100-PE	0.05	—	-0.01	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.50	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.95	—	—	—	—	—	—	—	—	—	—	—	—	0.01	—	—	-0.01	—	—

Notes: This table presents the quantile regression coefficients of each sector CDS index with respect to the covariates reported in the first column. The table includes only the statistically significant coefficients at the 5% confidence level. Quantile levels are reported in the second column. The sample period considered is January 2004 to December 2011

Table 6: Insert text here.

	MIN	MEAN	MEDIAN	MAX	25%	75%	5%	95%
0.05	-0.26	0.13	0.11	0.77	-0.04	0.25	-0.15	0.50
0.10	-0.09	0.20	0.15	0.69	0.04	0.35	-0.03	0.56
0.20	0.01	0.27	0.21	0.74	0.13	0.42	0.05	0.60
0.30	0.02	0.31	0.25	0.78	0.16	0.47	0.08	0.62
0.40	0.04	0.33	0.27	0.79	0.17	0.51	0.09	0.66
0.50	0.05	0.34	0.28	0.71	0.18	0.53	0.10	0.68
0.50	0.03	0.35	0.34	0.74	0.20	0.49	0.08	0.67
0.60	0.02	0.33	0.31	0.73	0.19	0.46	0.07	0.65
0.70	0.02	0.31	0.28	0.75	0.16	0.46	0.06	0.61
0.80	0.00	0.28	0.24	0.75	0.13	0.40	0.04	0.58
0.90	-0.08	0.21	0.17	0.75	0.07	0.34	-0.02	0.54
0.95	-0.26	0.16	0.12	0.81	0.01	0.31	-0.12	0.51

Table 7: Insert text here.

	BB_BBB	BBB_AAA	TS	REPO-TBILL	RISK_APP	TED	NYSE	TBOND5RATE	VIX	SP100_PE
0.050	0.266	0.225	0.090	-0.197	0.041	0.051	0.001	0.137	0.002	0.174
0.100	0.267	0.244	0.145	0.069	0.166	0.116	0.123	0.139	0.124	0.026
0.200	0.340	0.244	0.125	0.089	0.180	0.110	0.270	0.117	0.172	0.033
0.300	0.340	0.285	0.168	0.102	0.195	0.125	0.295	0.135	0.183	0.042
0.400	0.341	0.300	0.193	0.112	0.220	0.122	0.289	0.134	0.207	0.037
0.500	0.355	0.311	0.182	0.112	0.230	0.124	0.254	0.135	0.226	0.039
0.500	0.395	0.222	0.154	0.106	0.381	0.119	0.229	0.090	0.382	0.071
0.600	0.389	0.201	0.124	0.080	0.350	0.126	0.221	0.101	0.370	0.072
0.700	0.369	0.189	0.126	0.056	0.320	0.095	0.198	0.058	0.342	0.069
0.800	0.347	0.175	0.117	0.033	0.278	0.065	0.155	0.043	0.297	0.062
0.900	0.401	0.135	0.015	0.006	0.217	0.040	0.053	-0.141	0.233	0.171
0.950	0.362	0.131	0.046	-0.077	0.207	0.207	0.007	0.026	0.137	-0.101

Table 8: Insert text here.

		AUTOMOB	BANKING	BASICRES	CHEMIC	CONSTMAT	FINSERV	FOODBEV	HEALTCARE	INDLGDS	INSURAN	MEDIASEC	OILEGAS	PSNLHSLD	RETAILSEC	TECHNOL	TELECOM	TRAVLEI	UTILITIES
	Quantile	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
BB-BBB	0.05	1.86	0.21	—	0.26	0.39	0.93	0.22	0.23	0.29	0.99	1.04	0.31	0.56	0.46	0.48	0.58	1.62	0.34
	0.50	1.55	0.18	0.26	0.25	0.38	0.48	0.17	0.18	0.31	0.42	0.57	0.28	0.48	0.42	0.49	0.52	1.01	0.31
	0.95	3.78	0.27	0.41	0.30	0.49	1.42	0.23	0.26	0.38	1.02	1.36	0.35	0.73	0.62	0.65	0.61	1.53	0.41
BBB-AAA	0.05	—	—	—	—	—	—	—	—	—	—	0.60	—	—	—	—	—	—	—
	0.50	1.29	—	0.18	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.95	—	—	—	—	—	—	—	—	—	—	0.24	—	—	—	—	—	—	—
TS	0.05	-4.33	—	-0.73	-0.34	-0.21	-1.51	-0.11	—	—	-1.63	-1.27	—	—	—	—	—	—	—
	0.50	0.40	—	—	0.06	—	—	0.05	0.05	0.02	—	—	—	—	—	—	—	—	—
	0.95	5.78	—	1.23	0.73	—	—	0.23	—	—	—	2.03	0.18	0.57	0.62	0.68	0.14	1.76	—
LIQRISK	0.05	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	-0.10
	0.50	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.95	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
RISK-APP	0.05	—	0.01	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.50	—	—	0.00	—	0.00	—	0.00	0.00	—	—	—	0.00	—	—	—	—	—	0.00
	0.95	—	—	-0.02	-0.01	—	-0.02	-0.01	0.00	—	—	-0.04	-0.01	—	—	—	—	—	-0.01
TED	0.05	5.06	0.44	0.87	0.45	—	1.77	0.16	—	0.31	—	1.27	—	—	—	0.33	—	—	0.28
	0.50	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.95	-7.00	—	-1.49	-0.74	—	—	-0.28	—	-0.28	—	-2.62	-0.21	-0.60	-0.68	-0.70	—	-2.36	—
NYSE	0.05	—	-0.03	—	—	—	—	—	—	—	-0.05	—	-0.01	-0.02	—	-0.02	—	—	-0.01
	0.50	-0.04	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01
	0.95	—	-0.03	—	-0.02	-0.01	—	—	—	—	—	—	—	-0.02	—	-0.02	-0.01	—	—
TBOND5RATE	0.05	4.10	—	0.76	0.40	0.34	1.58	0.22	0.10	0.31	1.79	1.18	0.24	0.41	0.41	0.40	0.57	—	0.27
	0.50	0.30	—	0.10	0.05	0.14	0.17	—	—	0.11	0.15	0.20	0.11	0.17	0.14	0.13	0.24	0.40	0.09
	0.95	—	-0.30	-0.95	-0.52	—	—	-0.15	—	—	—	-1.32	—	—	-0.40	—	—	—	—
VIX	0.05	—	-0.01	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.00
	0.50	—	—	0.00	—	—	—	—	0.00	—	0.01	—	0.00	—	0.00	—	0.00	—	0.00
	0.95	—	—	—	—	0.01	—	0.01	0.00	—	—	—	0.01	—	—	—	—	—	0.01
SP100-PE	0.05	—	-0.01	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.50	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	0.95	—	—	—	—	—	—	—	—	—	—	—	—	0.01	—	—	-0.01	—	—

Table 9: Insert text here.

	From 2004	From 2007	From 2009
	P-value	P-value	P-value
S_AUTOMOB	0.000	0.000	0.003
S_BANKING	0.000	0.008	0.001
S_BASICRES	0.009	0.166	0.038
S_CHEMIC	0.001	0.000	0.047
S_CONSTMAT	0.064	0.993	0.252
S_FINSERV	0.000	0.002	0.000
S_FOODBEV	0.001	0.000	0.047
S_HEALTCARE	0.037	0.460	0.000
S_INDLGDS	0.003	0.027	0.013
S_INSURAN	0.000	0.005	0.676
S_MEDIASEC	0.000	0.000	0.432
S_OILEGAS	0.019	0.436	0.021
S_PSNLHSLD	0.013	0.842	0.352
S_RETAILSEC	0.000	0.189	0.002
S_TECHNOL	0.010	0.018	0.003
S_TELECOM	0.116	0.465	0.000
S_TRAVLEI	0.158	0.224	0.014
S_UTILITIES	0.003	0.002	0.000

Figure 2: Average rolling correlations

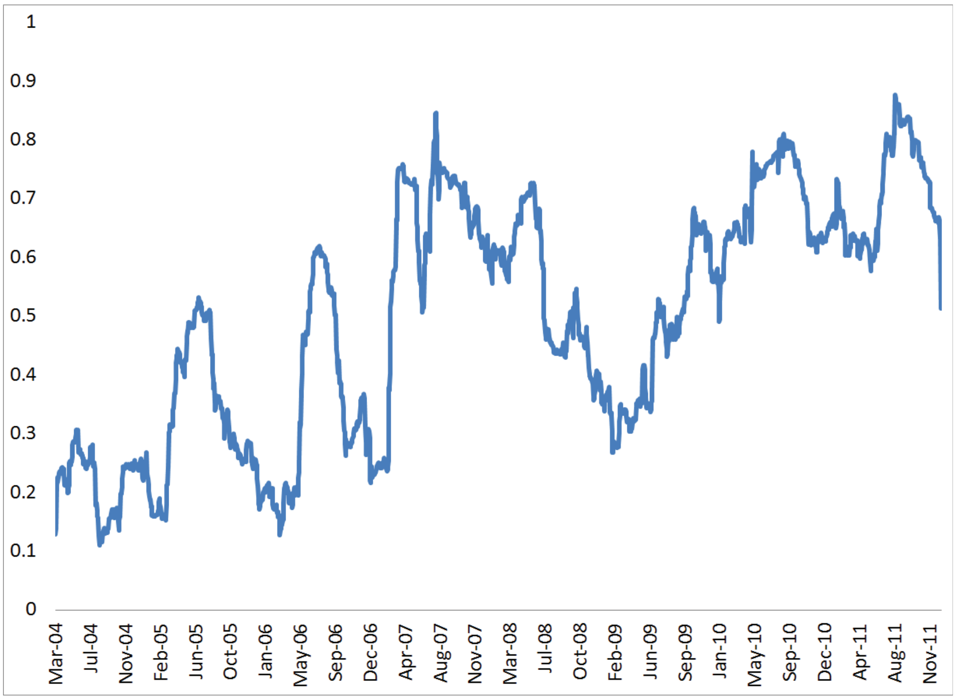

Figure 3: Principal Component Analysis

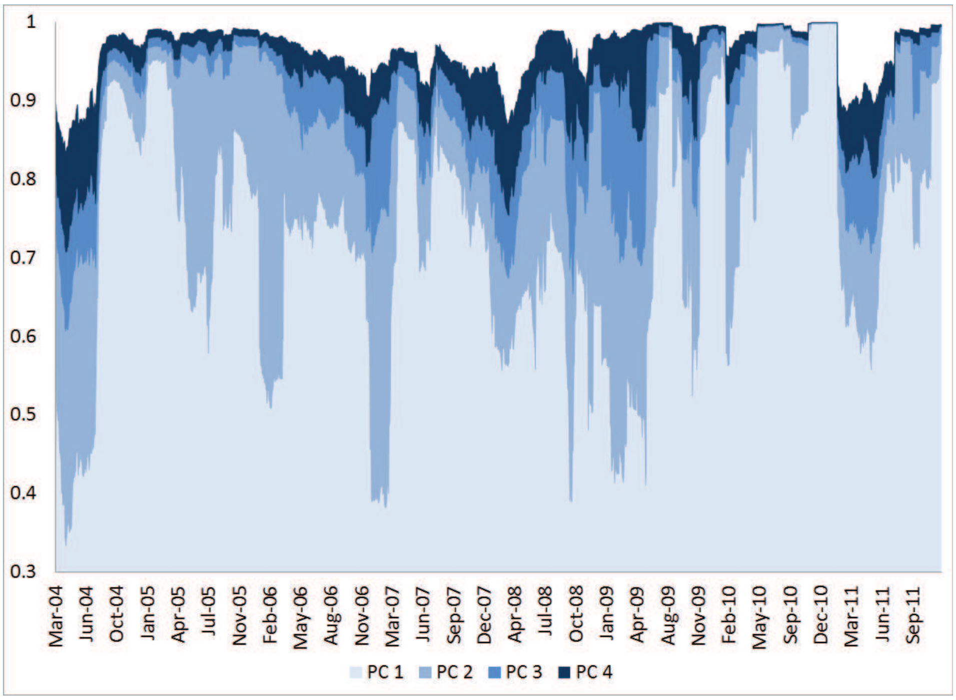

Figure 4: Figure 4a

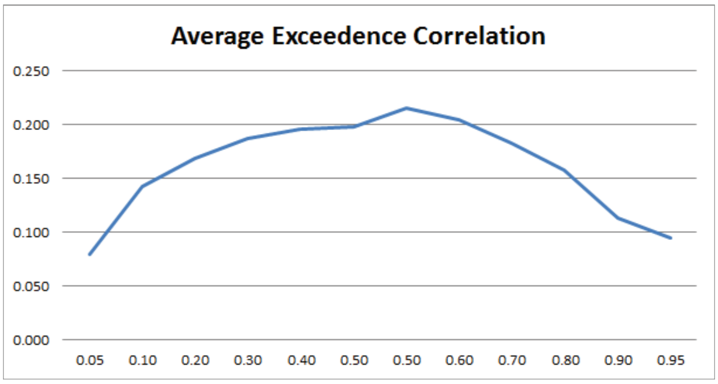

Figure 5: Figure 4b

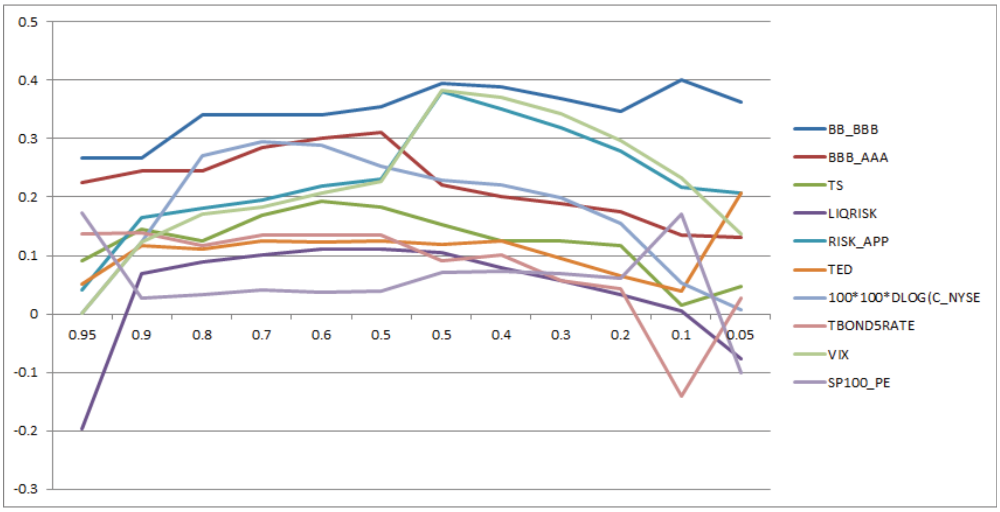

Figure 6: Number quantiles