Firm-Fundamentals, Economic Data, and a Bubble in the CDS Market

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Abstract

The events of the subprime crisis triggered significant price changes in almost all asset markets. This paper investigates the credit default swap (CDS) market over the period January 2002 until April 2008. In the course of time spreads reveal patterns comparable to an asset price bubble, which burst due to the events of the subprime crisis but already commenced in mid-2003. It suggests that beside other factors the market crisis induced investors to revalue individual positions resulting in significant price adjustments. On these grounds, three structural credit pricing models are employed to proxy for the fundamentally justified spread level. The deviation between market and model spreads is subsequently incorporated in a dynamic panel regression framework thereby controlling for macroeconomic as well as liquidity and implied volatility factors. The regressions report a persistent but mean-reverting effect in spread deviations providing empirical evidence that they do neither derive from noise nor are they constant but show typical patterns of a bubble in CDS markets. Furthermore, the results suggest possible improvements for structural credit pricing models.

JEL Classification: A11, C33, C52, D40, G12, G15.
Keywords: Credit Default Swaps, Asset Price Bubble, Structural Credit Pricing Models.

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I. Introduction

The events of the subprime crisis led to significant price changes for almost all asset classes. Increasing risk aversion together with unknown risks in investors' portfolios accounted for these. But what has happened since its start in mid-2007? Have investors always comprehensively evaluated their portfolio risk in the period before? This paper provides a possible explanation for the significant price changes concentrating on the credit default swap (CDS) market. It provides empirical evidence that market spreads reveal patterns comparable to an asset price bubble, which burst with the start of the subprime crisis suggesting contemporaneous revaluation of investors' portfolios what caused spreads to adjust to more reasonable levels again. Furthermore, the commencement of the bubble pattern in the CDS market is shown to have arisen in mid-2003 not observable in public indices because those have been initiated not until 2004. Note that the data sample over the concurrent period reveals patterns and levels very comparable to public indices and can therefore be regarded as representative, especially due to its size of almost 850,000 daily observations. The results are robust over economic and regional as well as industry sector and rating differences among firms.

The current literature on asset price bubbles is primarily limited to the stock market where the three approaches of rational bubbles, psychology of imperfect rationality and pure psychological determinants have evolved. Those are either based on research in psychology, incorporate firms' dividends or constitute a hybrid of both. Important examples include Shiller (1981), LeRoy and Porter (1981), West (1987, 1988), Diba and Grossman (1988a, b), Froot and Obstfeld (1991), and Driffill and Sola (1998). This paper suggests a different approach applicable to the CDS market. Three structural credit pricing models are implemented to proxy for the fundamentally justified CDS spread level by the rationale of the models accounting for the capital structure of the respective firm. Merton (1974) initiated the literature on structural credit pricing models, based on the results of Black and Scholes (1973), valuing credit risk as a put option on the firm's assets. Following his work, Black and Cox (1976) and Longstaff and Schwartz (1995) developed first-passage time models with an exogenous default barrier which also constitute the fundament for the CreditGrades model of Finger et al. (2002) incorporated in this study. According to Currie and Morris (2002), Yu (2006) and Duarte, Longstaff and Yu (2007), it depicts the industry benchmark since its publication in 2002. The second utilized model, developed by Leland and Toft (1996), is based on the work of Leland (1994) and has shown to produce CDS spreads very close to market observations in Ericsson, Reneby and Wang (2005) and Cserna and Imbierowicz (2008). Finally, the model of Zhou (2001) comprises asset value jumps to account for sudden market changes and has not yet been implemented by any other researcher. Note that due to their special capital structure in other studies often omitted financial firms are included in the analysis by means of an adjustment of their default barrier with all results remaining robust.

In line with the literature on rational bubbles, the conjecture of an asset price bubble in CDS markets relates to market spreads significantly below fundamentally justified values. It implies that investors are willing to accept low spreads for selling protection with the expectation of those decreasing even further. Their view is reinforced by the surge in (synthetic) structured credit derivatives over the time period investigated implying excess supply for protection. The estimated model spreads comply with this supposition reflected in an overestimation for all approaches. Over the complete sample horizon, the Leland and Toft model demonstrates the best replication abilities with an average deviation of 55 basis points (bps), while the CreditGrades and the Zhou model depart by 77 and 71 bps, respectively. Analyzing the results in more detail shows that spreads significantly deviate from market spreads for a presumed bubble period mid-2003 until mid-2007 whereas those deviations are considerably lower for the remainder.

Several studies suggest that in addition to firm-fundamentals, macro- as well as microeconomic factors also influence CDS spreads. Important work in the area includes Collin-Dufresne, Goldstein and Martin (2001), Hull, Predescu and White (2004), Longstaff, Mithal and Neis (2005), Kisgen (2006), Yu (2006), Avramov, Jostova and Philipov (2007), and Chen, Lesmond and Wie (2007). On the one hand, those determinants derive from pure macroeconomic data and on the other hand incorporate rating, liquidity and volatility effects. On this account, the subsequent analysis controls for these influences together with firm-specific effects in a dynamic panel regression employing the Generalized Method of Moments estimator proposed by Arellano and Bond (1991). It is subdivided into investment and non-investment grade ratings as well as geographical regions to additionally account for differences in those. The results provide empirical evidence for a persistent but mean-reverting deviation between market and model CDS spreads over the analyzed time horizon and therefore reject the optional assumptions of in general noisy or constant deviations. This result is robust over geographical regions as well as diverse deviation measures. Furthermore, although on average an overestimation is indicated, controlling for the factors mentioned above the models reveal an *underestimation* for the European and Asian region while they appear to be correctly specified for North American obligors. Overall, the results suggest regional differences in CDS markets. Other significant factors often incorporate forward-looking attributes in line with the studies of Norden and Weber (2007), Blanco, Brennan and Marsh (2005), Zhu (2006) and Norden and Wagner (2007) who show that CDS spreads comprise investors' expectations for the prospective development in credit markets. Moreover, they confirm the finding in Longstaff et al. (2005) that the default component in CDS does not account for the entire corporate credit spread.

The remainder is structured as follows. The second section gives an introduction to the employed structural credit pricing models. Thereafter, the data set is described with section four presenting the market and model spreads. The fifth part provides the results for the conjecture of an asset price bubble. Section six concludes.

II. The Models

Preliminaries

Let V_t, S_t, D_t, and K_t denote the asset value, the market value of equity, the amount of the total liabilities, and the default barrier of the associated firm at time t divided by the number of shares outstanding, respectively.[1] Correspondingly, σ_V and σ_S denote the annualized asset and equity volatilities. In addition, Δt symbolizes the time period between consecutive sampling points, r reflects the risk-free interest rate, and R denotes the recovery rate on the senior subordinated debt underlying the CDS initiated at time $t = 0$ with maturity T. Based on the results of Covitz and Han (2004) and Altman, Brady, Resti and Sironi (2005), I choose $R = 0.4$ within all models and furthermore use $T = 5$ and $\Delta t = 1/252$. The interbank offered rate of the respective firm's country proxies for the risk-free interest rate.

In general, financial firms exhibit a different capital structure compared to industrials. For this reason they are often excluded in studies employing structural pricing models. In contrast, I try to adjust their capital structure, such that adequate spreads are estimated following the

[1] For matters of simplification, the notation neglects theoretical differences between stochastic processes, random variables, observed and simulated samples, and estimates.

reasoning of the capital requirements of Basel I and the standardized approach in Basel II.[2] Financial firms' left side of the balance sheet mainly consists of customer loans which have to be secured with a minimum capital of 8 percent of risk-weighted assets. I assume that all credits granted to customers are financed by customer deposits and that equity funds the remaining valuables of financial firms. Therefore, the default barrier is not set at the amount of their total liabilities but at 8 percent of these. Although this is just a very approximate measure for the default barrier the results in Cserna and Imbierowicz (2008) suggest its appropriateness.

In the following, just the essential model ingredients are described with further details provided in the appendix. For an in-depth technical discussion the reader is referred to the respective paper.

The CreditGrades Model

In this model, V_t is assumed to follow a geometric Brownian motion with zero drift under the risk-neutral measure, i.e.

$$dV_t/V_t = \sigma_V \, dW_t,$$

where W_t is a Wiener process. The assumption of a zero drift results in stationary leverage ratios corresponding to Collin-Dufresne and Goldstein (2001). Within this approach, the default barrier is defined by $K_t = L \cdot D_t$ where L is a log-normal random variable with $\mathrm{E}(L) = \bar{L}$ and $\mathrm{Var}(\ln L) = \sigma_L^2$ revealed at the time of default. The randomness of the default barrier reflects uncertainty which arises from for example incomplete accounting information and results in higher short-term default probabilities.[3] The survival probability is denoted by q_t with $q_0 \neq 1$ due to uncertainty in the default barrier in $t = 0$. The asset volatility is derived by means of historical estimates of the respective firm's stock volatility. Although Cao, Yu and Zhong (2007) and Benkert (2004) have shown that implied volatility derived from option markets dominates historical volatility in forecasting the future volatility on individual stocks, I rely on the latter one for reasons of data availability and accuracy. The utilization of the daily observations of firms' respective equity and debt results in a time-series of asset volatilities.

[2] An overview of the history and the capital requirements under Basel I and II is provided in Hull (2007).
[3] A theoretically more appealing approach is given by Duffie and Lando (2001).

The Model of Leland and Toft

In this model, the asset value is assumed to follow a geometric Brownian motion under the risk-neutral measure, i.e.

$$dV_t/V_t = (r-\beta)dt + \sigma_V dW_t$$

where β denotes the asset payout rate which is approximated for each sampling point using $\beta = (div_t + ie_t)/(S_t + D_t)$ with div_t and ie_t denoting the dividend and the total interest expenses per share at time t. Based on the work of Leland (1994), the firm's total market value equals the asset value plus the value of tax benefits resulting from debt issuance less the value of bankruptcy costs. The associated firm continuously issues debt of constant maturity Y resulting in overlapping debt contracts outstanding, each serviced by a continuous coupon C. The resulting coupon payments are tax deductible at a rate δ and the realized costs of financial distress amount to a fraction α of the asset value in case of default. Note that in this model uncertainty is generated via an endogenous default barrier induced by stockholders' permanent evaluation if future cash flows suffice to meet future net debt service requirements. Based on Ericsson, Reneby and Wang (2005), I set $\delta = 0.2$, $\alpha = 0.15$, and $Y = 3.38$.

The Model of Zhou

The application of this model consists of a parameter estimation which is followed by a Monte Carlo approach. Let X_t denote the asset value of the associated firm at time t relative to the default barrier, i.e. $X_t = V_t/K_t$ with the assumptions $V_t = S_t + D_t$ and $K_t = D_t$. In Zhou (2001) X_t follows a jump-diffusion process given by

$$dX_t/X_t = (\mu - \lambda\nu)dt + \sigma dW_t + (\Pi - 1)dY_t$$

where μ is a drift and σ a volatility parameter, Y_t is a homogenous Poisson process with intensity λ, and Π is the log-normal jump-amplitude with $\ln \Pi \sim \mathrm{N}(\mu_\Pi;\ \sigma_\Pi^2)$. As mentioned in Scherer (2005) and Zhou (2001), this specification allows for the possibility of sudden changes in firms' asset value resulting in higher short term spreads. Accordingly, the default barrier is determined exogenously but uncertainty in recovery rates arises from the asset value jump process.

The parameter vector $\theta = (\mu, \sigma, \lambda, \mu_\Pi, \sigma_\Pi)'$ is estimated numerically via maximum likelihood for each firm followed by a Monte Carlo simulation, which incorporates the estimates of θ

and is based on simulated samples of the asset value under the risk-neutral measure. This procedure requires $3 \cdot m \cdot M$ pseudo-random variables for each observation where I use $m = 100$ and $M = 5{,}000$ for computation.

III. Data Description

The daily observations on CDS are collected from Bloomberg and cross-checked via Datastream for all firms available, where the 5-year term for senior subordinated debt is selected due to the largest liquidity in the CDS market. All cases with a standard deviation of zero for more than five consecutive trading days are removed from the sample together with firms with less than one complete year of observations. The data run from January 2002 to April 2008 which constitutes the longest time period to date in a study on CDS.

The required firm-fundamentals for the estimation of the CDS pricing models are obtained from the same data sources excluding firms with missing or zero debt. Note that all balance sheet data is lagged by one month to ensure no look-ahead bias. Since structural pricing models constitute the fundament in this analysis the dataset does neither include countries nor non-public firms. The interbank offered rate of the respective firm's country proxies for the risk-free interest rate due to reasons of data availability. Although not the exact measure, a sensitivity analysis reveals a rather low sensitivity on the pricing models' results. Finally, S&P and Moody's ratings and rating changes for each firm's senior unsecured debt are included.

This results in a final data sample of 759 firms with overall 848,301 daily observations. Table 1 shows that observations are approximately identically distributed over geographical regions with the U.S. constituting the most represented country closely followed by Japan. Note that a selection bias (and data mining) was avoided by collecting data on all constituents of major local as well as global indices accompanied by a Bloomberg list[4] from Markit™ Group on entities for which CDS pricing is available. Industrial firms represent the largest industry sector within the sample together with financials and firms producing consumer goods. More

[4] This list is a reference entity database project called "RED" and was developed in 2002 by Deutsche Bank AG, Goldman Sachs Group Inc. and JPMorgan Chase & Co. and sold in August 2003 to Markit Group. It links debt issuers to their obligations using Cusip-linked pair codes.

than 86 percent of the firms are rated investment grade but the large sample size contributes to a significant number of observations also for non-investment grade rated obligors.

Table 1: Number of Observations by geographical region, most represented countries and ratings over years, and Number of Firms by industry sector

The table displays on the left side the number of observations by geographical region as well as by the countries most represented in the data sample. On the right side the number of firms by industry group is shown. At the bottom, the number of observations for investment grade, non-investment grade and non-rated obligors are provided individually as well as on an aggregate yearly basis and for the complete time horizon.

North America	303,307
Europe	265,400
Australia & Asia	279,594
Total Observations	848,301
United States	286,344
Japan	243,713
Britain	69,379
France	50,664
Germany	38,540
Italy	20,404

Oil & Gas	33
Basic Materials	78
Industrials	134
Consumer Goods	125
Health Care	27
Consumer Services	108
Telecommunications	35
Utilities	57
Financials	127
Technology	35
Total Firms	759

	2002	2003	2004	2005	2006	2007	2008	2002 - 04/2008
Investment Grade	45,474	85,796	116,543	144,492	150,187	143,099	45,718	731,309
Non-Investment Grade	1,179	6,094	13,823	19,071	21,006	19,808	6,395	87,376
Non-Rated	1,979	4,310	6,864	8,028	4,842	2,923	670	29,616
Total Observations	48,632	96,200	137,230	171,591	176,035	165,830	52,783	848,301

The economic data is also obtained from Bloomberg and Datastream and additionally cross-checked via the publicly available publications of the respective statistical offices. The unemployment rate, inflation and industrial production are calculated as percentages while the consumer confidence, business confidence and leading economic indicators are either employed on an index level or based on survey data. For an analysis of the respective regions the data on the U.S. and Japan proxy for the North American and Asian region, respectively, whereas for Europe official data aggregates are utilized. The data in general reveal improving economic conditions in all regions beginning in 2003 until the emergence of the subprime crisis in mid-2007.

Table 2 displays the empirical mean and standard deviation of the economic data for each region. Note that the unemployment rate, inflation and industrial production are directly comparable among regions due to the same computation methodology. On the other hand, consumer confidence differs in scale because it ranges from [-100; 100] in the Euro area, from [0; 100] in the Asian region and for the U.S. an index with a base of 100 in the year 1985 reflects its value. This scale difference is also true for the business confidence indicator with a range from [0; 100] for the U.S. and Asia and from [-100; 100] for the Euro-Zone. The leading economic indicators are all provided on an index level and reflect the aggregate of numerous economic variables as for example manufacturers' new orders, building permits, supplier deliveries, initial claims for unemployment insurance, or average weekly manufacturing hours but also the interest rate spread, stock prices, and the real money supply. By nature, it exhibits some correlation to most other economic variables and a robustness check for collinearity is recommendable if including it conjointly with any of those in regressions.

Table 2: Economic Data by region over the time period January 2002 – April 2008

The table shows the mean and the standard deviation subdivided by geographical region for the respective variable. Data for the U.S. proxies for the North American region, data on the 12 initial monetary union member countries of the E.U. for the European region and data on Japan for the Asian region. Industrial production is calculated as year-on-year percentages while for unemployment and inflation percentage levels are employed. The consumer confidence index is based on survey data and provided as an index for the North American region with a base of 100 in 1985, for the European region it ranges from [-100; 100] and for the Asian region from [0; 100]. For business confidence survey data is applied, too, with a range from [0; 100] for North America and Asia and from [-100; 100] for Europe. The leading economic indicators are provided on an index level for all regions with a base of 100 in 2004 for the U.S, in 2003 for Europe and in 2004 for Japan.

	North America		**Euro Area**		**Asia**	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Unemployment	5.14	(0.52)	10.31	(0.90)	4.32	(0.44)
Inflation	2.92	(0.84)	2.21	(0.39)	0.03	(0.44)
Industrial Production	2.18	(1.05)	2.95	(2.33)	3.06	(2.47)
Consumer Confidence	96.39	(12.08)	-14.14	(5.14)	46.17	(3.99)
Business Confidence	50.94	(4.77)	-3.02	(5.99)	48.45	(2.31)
Leading Economic Indicators	100.66	(4.47)	104.54	(3.04)	98.89	(3.50)

IV. CDS Market and Model Spreads

In this section the average market CDS spreads and the model spreads for the CreditGrades, the Leland and Toft, and the Zhou model are presented irrespective of a possible mispricing in the CDS market. This will be investigated in the next section after a general overview has been provided. As described earlier, the models are based on firm-fundamentals and accordingly the results should be independent of the development in the CDS market.[5] Table 3 displays that on average all models overestimate actual market spreads. The Leland and Toft model exhibits the lowest deviation with 55 basis points (bps) followed by the Zhou model with 71 bps and the CreditGrades model with an average pricing error of 77 bps. A look at the specific rating intervals shows that the performance of the respective models differs significantly. The Leland and Toft model frequently underestimates market spreads for obligors rated BB- and lower what is also true for the Zhou model for rating classes below B+. For the remainder all models overestimate market spreads. Another noticeable result from Table 3 is the large standard deviation of spreads. It suggests a high variation in market spreads within rating classes and diminishes the interpretability of the replication abilities at the individual firm level by means of this table. Nevertheless, on the portfolio level the models replicate market spreads adequately especially in light of a presumable bubble in the CDS market within the observation period.

Various factors alongside which are not captured in the models could also account for deviations between model and market spreads and have already been discussed in the literature in more detail. Hull, Predescu and White (2004), Norden and Weber (2004), and Kisgen (2006) provide empirical evidence that negative rating reviews and announcements impact market spreads as well as capital structure decisions of managers. Furthermore, most macroeconomic factors are neglected in structural credit pricing models. The importance of these is verified by Collin-Dufresne, Goldstein and Martin (2001), Avramov, Jostova and Philipov (2007), Schaefer and Strebulaev (2004), Yu (2006), Amato (2005), and Longstaff, Mithal and Neis (2005). Moreover, market specific influences such as liquidity and non-standardized contractual terms could result in poor replication capabilities of the models emphasized in Packer and Zhu (2005), Tang and Yan (2006), Andritzky and Singh (2006), Davydenko (2007), and Chen, Lesmond and Wie (2007). Other possible impacts which have been analyzed intensively for the stock market but not yet for CDS are the influences of investor psychology and trading behavior on prices. As already mentioned, the fifth section will address these factors in more detail.

[5] Of course, independence exists only theoretically. Market and model spreads are related via the price and volatility of the respective firm's market capitalization which are input factors for the model estimations as well as they influence market spreads as shown in Campbell and Taksler (2003), Ericsson, Jacobs and Oviedo (2005), and Schleicher (2006).

Table 3: Mean and Standard Deviation (STD) of Market and Model Spreads in basis points by rating class for the period 2002 – April 2008

The table displays the mean and the standard deviation (STD) of CDS market spreads and model spreads computed via the CreditGrades, the Leland and Toft, and the Zhou model, subdivided into rating classes, as well as broad ratings and for the whole data sample. Furthermore, the corresponding number of observations and the difference of the respective model to the market spread are shown.

			CDS Spreads								**Difference of Model minus Market Spread**					
			CDS Market		CreditGrades		Leland & Toft		Zhou		CreditGrades		Leland & Toft		Zhou	
Rating Class		Observations	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
NR	Non-rated	29,616	133	(593)	173	(437)	158	(493)	167	(283)	39	(290)	27	(395)	34	(496)
D		1,571	125	(541)	266	(609)	224	(314)	163	(240)	141	(148)	151	(347)	38	(405)
CC		6	2,074	(497)	2,390	(29)	1,601	(42)	1,789	(0)	316	(514)	-472	(471)	-284	(497)
CCC-		3	2,619	(761)	2,742	(555)	1,456	(307)	808	(286)	124	(365)	-736	(53)	-1,811	(503)
CCC		361	851	(439)	1,202	(289)	586	(257)	90	(125)	351	(228)	-266	(201)	-762	(321)
CCC+	Non-Investment Grade (Non-IG)	1,569	593	(282)	1,161	(767)	730	(1,377)	304	(504)	568	(691)	138	(1,271)	-290	(632)
B-		6,404	467	(215)	642	(397)	386	(210)	370	(288)	175	(335)	-75	(229)	-97	(325)
B		5,264	289	(168)	341	(363)	203	(181)	208	(277)	52	(312)	-82	(189)	-81	(310)
B+		6,517	356	(310)	415	(439)	268	(243)	373	(357)	58	(318)	-79	(224)	16	(425)
BB-		14,061	263	(176)	313	(293)	256	(313)	307	(414)	49	(265)	-7	(324)	43	(422)
BB		17,646	190	(197)	281	(325)	213	(237)	261	(310)	91	(287)	24	(253)	70	(331)
BB+		33,974	142	(162)	273	(642)	259	(737)	215	(303)	131	(600)	117	(699)	73	(299)
BBB-		76,629	95	(107)	205	(436)	194	(522)	203	(316)	110	(413)	99	(500)	108	(321)
BBB		117,966	64	(68)	136	(257)	119	(273)	140	(237)	72	(247)	55	(264)	77	(231)
BBB+		115,438	51	(53)	168	(530)	126	(385)	135	(216)	117	(522)	75	(370)	84	(221)
A-		114,079	37	(40)	126	(288)	106	(219)	156	(298)	89	(283)	69	(211)	119	(298)
A	Investment Grade (IG)	116,311	32	(47)	86	(226)	78	(165)	85	(198)	54	(223)	46	(165)	53	(200)
A+		73,917	28	(43)	79	(180)	71	(140)	98	(181)	51	(179)	43	(143)	69	(185)
AA-		54,036	25	(53)	58	(74)	57	(77)	79	(165)	32	(73)	32	(83)	54	(169)
AA		34,224	22	(50)	63	(84)	61	(81)	58	(120)	41	(74)	38	(80)	35	(126)
AA+		18,993	19	(21)	34	(62)	31	(62)	69	(208)	15	(62)	12	(65)	49	(210)
AAA		9,716	21	(21)	79	(89)	65	(70)	12	(30)	58	(87)	44	(69)	-9	(32)
Non-IG		87,376	231	(237)	343	(522)	265	(539)	262	(335)	112	(452)	37	(517)	31	(362)
IG		731,309	46	(63)	120	(320)	104	(283)	123	(236)	75	(310)	59	(271)	78	(236)
Total		848,301	68	(158)	145	(357)	123	(332)	139	(254)	77	(327)	55	(311)	71	(265)

Table 4 displays average market and model spreads classified by industry sector to ensure that no specific sector biases the results. It reveals comparable patterns to the rating level. All models overestimate market spreads over industry categories but in general perform well on the portfolio level while market as well as model spreads show significant standard deviations. Market spreads are replicated best for firms related to oil and gas, consumer services and utilities by the CreditGrades, the Leland and Toft, and the Zhou model, respectively. The Zhou model reveals the largest deviation from market spreads for industrials while the two remaining deviate most for firms related to consumer goods. Note that the adjustment for financial firms produces results in line with the overall patterns of the data set.

Table 4: Mean and Standard Deviation of Market and Model Spreads in basis points by industry sector over the period January 2002 – April 2008

The table provides the mean of market and model spreads and the standard deviation in brackets beneath, by industry groups. The difference of model minus market spread is calculated at the individual firm level and subsequently aggregated at the industry level. This infrequently results in slight deviations compared to the aggregate difference due to very few not estimable observations for the Leland and Toft model and also rounding.

	CDS Spreads				**Difference of Model minus Market Spread**		
	Market	CreditGrades	Leland & Toft	Zhou	CreditGrades	Leland & Toft	Zhou
Oil & Gas	41	52	54	132	11	12	90
	(44)	(84)	(86)	(188)	(83)	(88)	(182)
Basic Materials	68	121	109	149	53	41	81
	(126)	(185)	(134)	(240)	(126)	(114)	(241)
Industrials	53	169	156	199	116	103	146
	(76)	(221)	(198)	(326)	(204)	(194)	(317)
Consumer Goods	100	246	209	167	146	112	67
	(320)	(472)	(562)	(277)	(378)	(505)	(347)
Health Care	52	75	62	121	23	10	69
	(101)	(192)	(219)	(245)	(170)	(216)	(247)
Consumer Services	85	135	88	132	50	3	48
	(106)	(434)	(166)	(225)	(437)	(176)	(232)
Telecommunications	85	157	118	131	73	33	47
	(111)	(340)	(214)	(231)	(337)	(218)	(221)
Utilities	47	103	88	68	56	41	21
	(66)	(128)	(155)	(162)	(127)	(160)	(163)
Financials	44	106	93	82	62	49	38
	(75)	(476)	(462)	(203)	(456)	(443)	(207)
Technology	91	115	109	181	25	18	90
	(147)	(139)	(121)	(276)	(123)	(137)	(249)

V. Fundamentals and a Bubble

Over the sample period the notional amount outstanding in the CDS market increased significantly from approximately \$2 trillion in 2002 to \$62.2 trillion at the end of 2007 with no deceleration in growth optionally induced by the subprime crisis.[6] On the one hand, its augmentation was driven by an increasing demand for protection on the underlying obligations which ceteris paribus should have driven CDS market spreads up. Buying protection implies shorting the underlying obligation and is therefore substantially easier implemented in CDS compared to bonds. On the other hand, a look at publicly available credit default swap indices reveals a converse picture. In the upper row, Figure 1 displays the progression of the well-known CDX and iTraxx indices since their initiation and reveals two elementary problems. First, an official index for the Asian region does not exist to date. And second, the available indices have been initiated not until the years 2004/2005 and therefore reflect a rather short time horizon. Nevertheless, they show that CDS market spreads have been quite low until the start of the subprime crisis in mid-2007 with a short deviation from tranquility in mid-2005.

In the lower row, Figure 1 provides the CDS spread level of the employed data set and reveals a comparable pattern and also level to the CDX and iTraxx indices arguing for the representativeness of the sample.[7] It additionally shows that CDS spreads have not always been at low levels until the start of the subprime crisis but decreased significantly since 2003. This is also confirmed by bank internal credit derivative indices and anecdotal evidence.[8] The progression over time suggests that the supply of credit protection significantly exceeded the demand since 2003. The explanations for this development are manifold. First, the overall economic conditions improved over this time period what is confirmed by the economic variables described earlier on. This resulted in less expected defaults and therefore decreasing demand for credit protection. Second, investors shifted large parts of their (long) credit exposure from the bond to the CDS market due to the larger liquidity and associated quicker response to market events, a finding confirmed in Norden and Weber (2007), and Longstaff, Mithal and Neis (2005). The third and presumably most significant influence for the decline

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[6] The figures for 2007 resort to the International Swaps and Derivatives Association's (ISDA) annual meetings on April 16, 2008. It mentions a 37 percent growth for CDS from mid-2007 until year end strongly supporting continued growth in single-name credit derivatives despite the subprime crisis which had strong negative effects on the liquidity and market volume of many structured credit derivates.

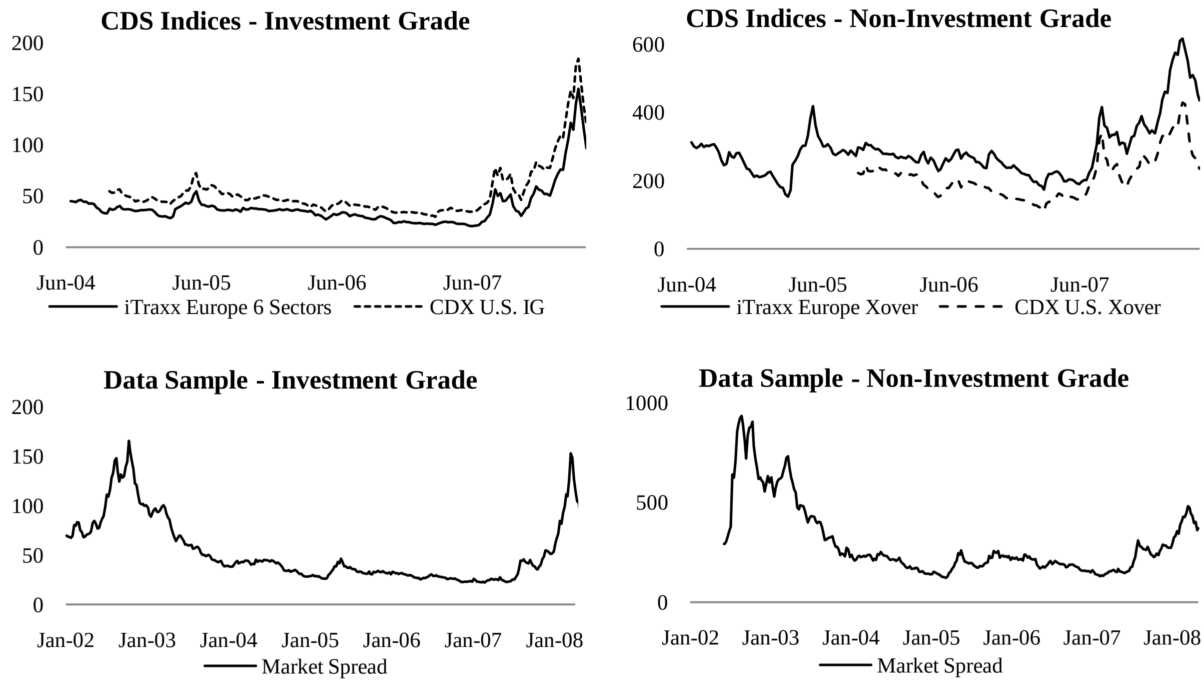
[7] A correlation analysis of weekly CDS index and aggregated sample spreads subdivided into broad rating classes as well as geographical regions supports this since in both North America and Europe the correlation coefficient is almost 0.99 and 0.95 in the investment and in the non-investment grade rating class, respectively.

[8] Although the data for bank-internal indices is present it cannot be provided here due to confidentiality reasons.

in CDS spreads is the evolvement of structured credit derivatives as for example collateralized debt obligations (CDO). These have often been set up synthetically implying that credit protection had to be sold in the CDS market thereby driving market spreads down.[9] The emergence of the subprime crisis in mid-2007 on the other hand caused CDS spreads to significantly increase partly explainable by increasing risk aversion and declining liquidity but also by supposable re-evaluation of investors' portfolios including credit derivative positions. In light of the very low spread levels from mid-2003 until mid-2007 and the progression of these over the time period investigated Figure 1 in general argues for a bubble in CDS markets.

Figure 1: CDS Indices – CDX and iTraxx vs. the Data Sample

The figure provides the progression of the CDX and iTraxx indices in the upper and of the data sample in the lower row. For the investment grade category the iTraxx Europe was chosen which is composed of 125 equally-weighted investment grade entities from 6 sectors: Autos, Consumers, Energy, Financials, Industrials, and TMT (technology, media and telecommunications). The Dow Jones CDX North America Investment Grade Index is composed of 125 investment grade entities, distributed among 6 sub-indices: High Volatility, Consumer, Energy, Financial, Industrial, and TMT. The non-investment grade category is represented by the iTraxx Europe Crossover and the Dow Jones CDX North America Crossover which consist of 40 and 35 obligors, respectively. For each index the respective on-the-run series reflects the progression over the time horizon.



The literature on asset price bubbles is primarily limited to the stock market where the approaches of rational bubbles, psychology of imperfect rationality and pure psychological

[9] A nice overview on the mechanics of structured credit derivatives is provided in e.g. Duffie and Singleton (2003), Hull (2007) or Chacko et al. (2006).

determinants have evolved. While the third one is essentially based on research in psychology the second constitutes a hybrid of psychological influences and asset pricing methodologies.[10] Given the arguments above, the most promising avenue of research on a presumable bubble in CDS markets appears to be the approach of rational bubbles. Regarding stocks, it implies that investors are willing to pay more than fundamentally would be justified due to their expectation of prices increasing furthermore. This reasoning translates for the CDS market into investors accepting low premiums for selling credit protection because they assume spreads to further decrease in the future. Their view is for example supported by the facet of low market interest rates over the analyzed time horizon and the accompanied high demand for (synthetic) structured credit products. To test for rational bubbles, four main econometric techniques have been suggested to date.[11] First, Shiller (1981), and LeRoy and Porter (1981) suggest the variance bounds test which compares the variance of the dividend discount model price to the ex-post rational price. Second, West (1987, 1988) regresses stock prices on dividends including an autoregressive term and compares his results to the theoretical relationship between those derived via the Euler equation to determine the adequate discount rate. The third approach relates to the work of Diba and Grossman (1988a, b) who formulate a framework to test for the absence of bubbles via integration and cointegration tests of stocks and dividends. And fourth, Froot and Obstfeld (1991) test for intrinsic bubbles by means of exclusively exogenous determinants of asset prices with the bubble tied to the level of dividends. Their work is expanded by Driffill and Sola (1998) who additionally introduce regime-switching. Examining the approaches on bubbles to date, it is apparent that although to some extent transferable they cannot be directly applied to CDS markets attributed to the missing proxy for dividends.

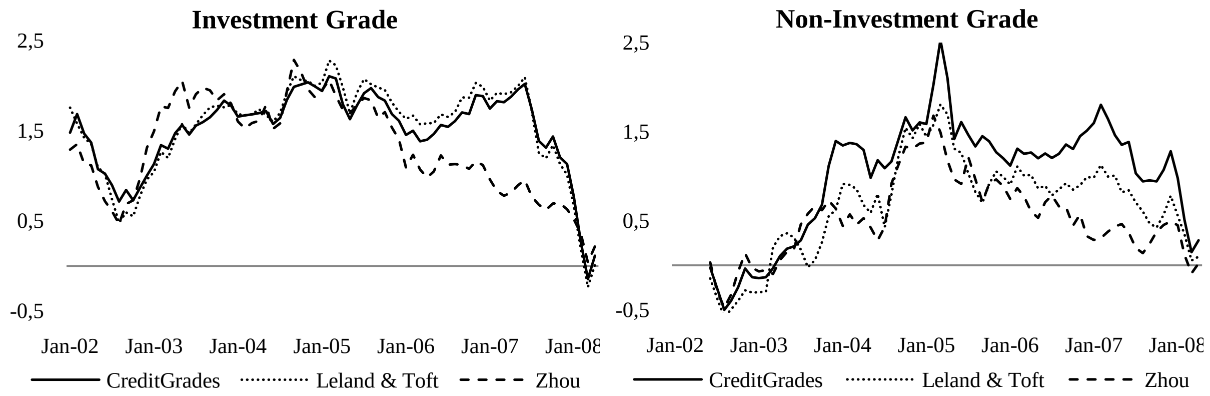
All models employed in this study account for the capital structure of the respective obligor implying that they are essentially based on firm fundamentals. Although not incorporating rating effects, macroeconomic data or liquidity impacts they are able to provide a first indication for the fundamentally justified CDS spread level. Following this reasoning their deviation from market spreads could serve as a measure for a presumable bubble. Figure 2 illustrates the relative deviation between the market and the respective model spread over the period January 2002 to April 2008. It suggests a bubble in the CDS market which started in mid-2003 and ended in mid-2007 induced by the events of the subprime crisis. Note that

[10] An elaborate overview on asset-pricing theories based on imperfect rationality is given in Hirshleifer (2001).
[11] Gürkaynak (2008) provides an in-depth discussion of the literature on rational bubbles.

although the models differ significantly in their default barrier assumption and asset value process they all describe a comparable deviation pattern.

Figure 2: Relative Deviation between Market and Model Spreads by rating category

The figure provides the progression of the relative deviation between market and model spreads calculated daily at the individual firm level and aggregated to monthly data by investment and non-investment grade rating category. The relative deviation is calculated for each model as the difference of model minus market spread normalized by the market spread. The figure has been adjusted for outliers larger 15 which rarely occur but could possibly distort the results.



Although supported graphically, the conjecture of a bubble in CDS markets could also result from model misspecification, missing factors or inadequate input variable assumptions. As already mentioned in the second section, I try to account for biases in the latter by employing values based on findings in prior literature to avoid the aspect of overfitting and preserve neutrality. A regression technique could control for the two former if it is able to show a non-constant deviation between market and model spreads and account for firm-specific as well as economic impacts. The well-known Generalized Method of Moments (GMM) estimator proposed by Arellano and Bond (1991), which includes lags of the dependent and predetermined variables as instruments, complies with these conditions. It allows for a lagged dependent variable to capture a dynamic effect and model a partial adjustment thereby removing autocorrelation in the data. The estimator is consistent if there is no second-order serial correlation of the first differenced equation where the proposed test of Arellano and Bond (1991) is applicable. Additionally, the validity of the instruments has to be ensured with for example Sargan's (1958) test for over-identifying restrictions.

In the following, the relative deviations between market and model spreads will be regressed on their first lag in a dynamic panel regression to capture the persistence in deviation and ensure that it does not result from pure noise or outliers at the individual firm level. To confirm the conjecture of a CDS market bubble, the estimated coefficient should be within the range (0; 1) because i. a value equal to zero rejects a bubble in CDS markets, ii. a value larger than one indicates an exploding process and accordingly suggests an increasing deviation of market and model spreads over time, and iii. a value equal to one indicates a unit root process implying stochastic model misspecification with the variance of deviations diverging to infinity. Controlling for various factors not captured in the models the constant thereby proxies for mistaken model input variable assumptions and further missing (constant) influences on CDS spreads. If it was insignificantly different from zero the model would be perfectly specified and, as such, able to fully replicate market spreads given the present control variables.

The employed macroeconomic variables can be classified into pure economic data (unemployment rate, inflation, and industrial production) and indicators for the expectation of future economic developments (consumer confidence, business confidence, and leading economic indicators). Additionally, the relative CDS bid-ask spread[12] is included to proxy for the respective CDS' liquidity. Furthermore, as mentioned earlier, Benkert (2004) and Cao, Yu and Zhong (2007) have shown that implied volatility derived from option markets dominates historical volatility in terms of spread replication. Due to reasons of data availability it cannot be included in the model estimations and therefore implied volatility indices[13] serve as a measure for possible replication improvements if including implied rather than historical volatilities. While the Arellano-Bond estimator controls for firm-specific effects, the models are estimated separately for North American, European and Asian firms which are furthermore classified into investment and non-investment grade ratings to also account for regional as well as broad rating class differences.

Table 5 reports the estimated coefficients and provides empirical evidence for the initial conjecture of a bubble in the CDS market. All values for the lagged relative deviation between market and model spread are significant at the 1% level and range within the interval (0; 1) arguing for a persistent but mean-reverting discrepancy between market spreads and firm fundamentals. Since the regressions are based on quarterly data aggregates, this result suggests that an adverse movement between the CDS market and firm fundamentals prevailed

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[12] The relative bid-ask spread is calculated as the difference between ask and bid prices normalized by the market spread.

[13] The VIX Index is applied to North American and also Asian firms because no implied volatility index for Asia exists to date. It includes implied volatilities for the constituents of the S&P 500 and is provided by the Chicago Board Options Exchange (CBOE). For European firms the Dow Jones Euro Stoxx 50 Volatility Index is employed which is a measure for market expectations of near-term volatility based on options on the constituents of the DJ Euro Stoxx 50. The indices reveal a correlation coefficient of 0.90 what suggests the VIX Index as a possible proxy for the Asian region due to the worldwide interdependencies of capital markets.

for several months in line with the graphical results in Figure 2. In most instances, the estimations indicate stronger persistence for investment grade rated firms and accordingly a longer bubble period once a possible misvaluation emerged. Several explanations arise for this finding. As the demand for credit derivatives surged the CDS market volume, for the most parts, was concentrated on obligors in the investment grade category. Accordingly, those were better suited for the initiation of (synthetic) structured credit products resulting in a strong demand to sell credit protection on these obligors. Therefore, a presumable bubble could have started earlier in the investment grade class. But it should also have persisted for a longer time period because many investors did not fully account for the contingent loss-given-default (LGD) payment at the peak of the presumable exaggeration. When the subprime crisis emerged they adjusted their portfolios first for obligors where the largest losses could be presumed caused by near-term LGD payments. This led to an earlier re-adjustment of CDS spreads for very risky non-investment grade rated obligors due to the increasing demand to unwind the existent positions often accomplished through buying protection on the same obligor and thereby driving market spreads up. Furthermore, investors' and especially structured credit derivatives initiators' risk aversion possibly partly accounted for the strong persistence for investment grade rated obligors. Anecdotal evidence confirms that many equity tranches of CDOs have been sold to investors with the reputation of the respective initiator at risk. Accordingly, the overall CDO portfolio was aligned with relatively low expected aggregate defaults suggesting that investment grade rated obligors preponderated.

The employed structural pricing models in large part appear to be correctly specified for North American firms but reveal an *underestimation* for the remaining regions. Although graphically a prevalent overestimation would be expected controlling for macroeconomic, liquidity and implied volatility effects for European and Asian firms the models mostly seem to generate spreads lower than market counterparts. Note that the level of underestimation is comparable within but different between regions. These findings suggest differences for the CDS markets among regions. While the models together with the present control variables in general seem to be able to explain CDS spreads for North American obligors, either more factors[14] or calibration adjustments for some model input variables are required to account for the deviations between market and model spreads in the European and Asian region. The regional differences in CDS markets will not be further analyzed here but provide a promising avenue for future research.

[14] The factors in question should naturally have a constant effect on the deviation between market and model spreads and are therefore not easily identified.

Table 5: A Bubble in CDS Markets controlling for Missing Input Variables and Model Misspecification

The table shows a dynamic panel estimation of quarterly aggregated data at the firm level with significances determined from heteroscedasticity-robust standard errors. The relative deviation between market and model CDS spread is regressed on its first lag and control variables not captured in the models. The estimation is implemented using GMM following Arellano and Bond (1991). The test for no 2nd order autocorrelation was also proposed by those and should not be rejected to ensure a consistent estimation. The Sargan (1952) test of valid over-identifying restrictions based on the two-step estimator suggested by Arellano and Bond (1991) does not reject the over-identifying restrictions in all regressions, as required. Macroeconomic variables are employed as explained in Table 2 while the relative bid-ask spread derives from the difference of ask minus bid normalized by the market spread. For implied volatility the VIX index is utilized for North America and Asia and the Dow Jones Euro Stoxx 50 Volatility Index for Europe. The significance of the coefficients being different from zero is indicated by * = 10%-level; ** = 5%-level; and *** = 1%-level.

		North America			Europe			Asia		
		CreditGrades	Leland & Toft	Zhou	CreditGrades	Leland & Toft	Zhou	CreditGrades	Leland & Toft	Zhou
Investment Grade	Relative Deviation $_{t-1}$	0.830 ***	0.823 ***	0.799 ***	0.528 ***	0.693 ***	0.778 ***	0.696 ***	0.610 ***	0.730 ***
	Unemployment Rate	-1.061 ***	-0.639 ***	-0.484 **	-0.271 ***	-0.191 **	-0.091	-3.122 ***	-3.394 ***	-5.214 ***
	Inflation	0.405 ***	0.246 ***	0.288 ***	0.140	0.323 ***	0.548 ***	-0.418 ***	-0.538 ***	0.623 ***
	Industrial Production	0.015	-0.004	0.001	-0.206 ***	-0.124 ***	-0.189 **	0.258 ***	0.247 ***	0.386 ***
	Consumer Confidence	-0.028 ***	-0.022 ***	-0.017 ***	-0.109 ***	-0.084 ***	-0.083 ***	-0.100 ***	-0.171 ***	0.095 *
	Business Confidence	0.109 ***	0.076 ***	0.086 ***	0.182 ***	0.129 ***	0.189 ***	0.013	0.065	-0.007
	Leading Economic Indicators	-0.040	-0.035	-0.078 ***	0.147	0.037	-0.071	-0.177 ***	-0.157 ***	-0.513 ***
	Relative Bid-Ask Spread	0.052 ***	0.036 ***	0.022 *	0.045 ***	0.035 ***	0.091 **	0.022 ***	0.035 ***	0.042 *
	Implied Volatility	-0.023	-0.017	-0.021 **	-0.054 ***	-0.039 ***	-0.033 ***	-0.230 ***	-0.259 ***	-0.268 ***
	Constant	-0.023	-0.005	0.021	-0.133 ***	-0.095 ***	-0.096 ***	-0.284 ***	-0.322 ***	-0.542 ***
	Observations	3,655	3,655	3,655	3,215	3,198	3,215	3,571	3,571	3,571
	Firms	234	234	234	198	197	198	267	267	267
	2nd order autocorrelation test (p-value)	0.146	0.127	0.110	0.418	0.067	0.052	0.659	0.093	0.781

		North America			Europe			Asia		
		CreditGrades	Leland & Toft	Zhou	CreditGrades	Leland & Toft	Zhou	CreditGrades	Leland & Toft	Zhou
Non-Investment Grade	Relative Deviation $_{t-1}$	0.578 ***	0.557 ***	0.545 ***	0.586 ***	0.566 ***	0.781 ***	0.475 ***	0.471 ***	0.834 ***
	Unemployment	-0.129	0.104	0.018	-0.036	0.064	-0.085	-5.528 ***	-8.042	-6.573 **
	Inflation	0.313 ***	0.225 ***	0.174 ***	0.491 ***	0.235	0.639 ***	-0.276	1.072	2.209 **
	Industrial Production	-0.009	0.000	0.021	-0.217 ***	-0.116 **	-0.145	0.195 **	0.157	0.071
	Consumer Confidence	0.005	-0.005	-0.002	-0.034 *	-0.020	-0.032	0.071	0.090	0.348
	Business Confidence	0.073 ***	0.067 ***	0.045 ***	0.103 ***	0.071 ***	0.073	0.294	0.679	0.325
	Leading Economic Indicators	-0.042	-0.011	-0.054 *	0.169 *	0.044	0.247 *	-0.453 ***	-0.813 **	-0.685 ***
	Relative Bid-Ask Spread	0.051 ***	0.037 ***	0.020 **	0.081 ***	0.062 ***	0.154 **	0.022	-0.012	0.002
	Implied Volatility	-0.027 ***	-0.016 ***	-0.020 *	-0.044 ***	-0.034 ***	-0.037 ***	-0.127 ***	-0.199	0.005
	Constant	0.025	0.028 ***	0.027	-0.084 ***	-0.041	-0.115 **	-0.466 ***	-0.842	-0.652 **
	Observations	672	668	672	379	379	379	268	268	268
	Firms	69	69	69	36	36	36	32	32	32
	2nd order autocorrelation test (p-value)	0.298	0.269	0.249	0.207	0.183	0.140	0.928	0.432	0.453

The control variables largely indicate the same direction of influence over models, ratings and regions arguing for the robustness of the results. While in general an increase in the unemployment rate, consumer confidence, the leading economic indicators, liquidity and implied volatility reduces the level of deviation between market spreads and firm fundamentals, a rise in business confidence amplifies it. The influence of inflation and industrial production is not completely clear among regions. Note that all results on the persistence of spread deviations and also model misspecification are robust to the exclusion of the control variables. A possible bias in the regressions could arise from the liquidity proxy as it is derived through normalization with the market spread which is also included in the dependent variable. All reported estimations control for this possible endogeneity by the inclusion of lagged values of the liquidity proxy as instruments. As mentioned earlier, the leading economic indicators are correlated to most of the other variables employed and could slightly distort the coefficient estimates and standard errors due to potential collinearity. Furthermore, the consumer and business confidence indicators are based on survey data and could possibly contain measurement errors. Excluding those variables individually as well as altogether nevertheless does not change the derived effects confirming the robustness of the estimations. Further biases could arise from specific industry sectors especially via financial firms due to the adjustment of their capital structure. Excluding those, as well as industry sectors which highly over- or underestimate market spreads, also leaves the basic results unchanged. Additionally, the computation of the relative deviation between market and model spreads implies the apparent shortcoming of a theoretical range $[-1; \infty)$ and accordingly is not equally distributed for deviations below and above market spreads. On these grounds, the same analysis is conducted for log-deviations and also differences delivering overall very comparable results to the presented.[15]

The findings clearly suggest further improvements for structural credit pricing models. First, they show that macroeconomic conditions should be incorporated where especially inflation and implied volatility as well as consumer and business sentiment for North America and Europe, and the leading economic indicators for Asia indicate a significant impact on replication accuracy. These variables comprise features to signal the future economic development and accordingly are well-suited for the CDS market. This is confirmed by the

[15] Although the results are very comparable among relative deviations, log-deviations and differences the former reveal the most consistent estimations regarding the no-second-order autocorrelation condition of the Arellano and Bond (1991) estimator. Log-deviations and differences sometimes show second-order autocorrelation what implies that additional lags would be required for those regions or ratings. Therefore to remain consistent and maintain comparability, relative deviations are presented.

studies of Norden and Weber (2007), Blanco, Brennan and Marsh (2005), Zhu (2006) and Norden and Wagner (2008) who have shown that CDS lead the bond as well as the loan market. Their findings highlight that CDS spreads comprise investors' expectations for the prospective development in credit markets which is highly correlated to the expected future economic conditions. Second, the significance of the liquidity proxy confirms the findings of Longstaff et. al (2005) that the default component in CDS does not account for the entire corporate credit spread. Accordingly, model spreads should be adjusted to measures of illiquidity to improve a replication of market spreads. And third, the significance of the implied volatility proxy is in line with afore mentioned prior studies and suggests further advancements by its incorporation. Surprisingly, this result is not confirmed in all regressions and rather small for firms based in North America and Europe denoting historical volatilities as a potential proxy for these. Furthermore, one important factor for the estimation of structural credit pricing models has to be added to the current literature which is the possible occurrence of market bubbles. Table 6 provides empirical evidence that the models employed in this study deliver results closer to market spreads out of the presumed bubble period mid-2003 to mid-2007 for almost all rating categories. As the CDS market continues to grow, for example facilitated by the currently intended listing of credit derivatives, this area of research will remain exciting.

Table 6: ***Difference of Model minus Market Spreads in basis points by ratings subdivided for a presumed bubble period from mid-2003 until mid-2007***

The table shows the difference of the respective model minus the market CDS spread in basis points for defined rating intervals as well as the complete sample. The bubble period is defined as the time period between 06/2003 – 06/2007 including these months while the number of observations is provided for the complete time horizon. Note that the number of observations for the respective rating classes does not add up to the "Total" row because non-rated issuers are also included there.

	Observations	**CreditGrades**		**Leland & Toft**		**Zhou**	
		No Bubble	Bubble	No Bubble	Bubble	No Bubble	Bubble
BB+ and below	87,376	55	128	-19	53	-79	62
BBB- to BBB+	310,033	70	108	39	86	61	96
A- to A+	304,307	75	63	46	57	67	87
AA- and above	116,969	25	38	15	39	20	52
Total	848,301	64	82	34	63	45	81

VI. Conclusion

This paper investigates the global CDS market over a time horizon spanning more than six years and provides empirical evidence for market spread patterns which suggest a bubble from mid-2003 to mid-2007. For this purpose, the CreditGrades (2002), the Leland and Toft (1996) and the Zhou (2001) model are implemented to proxy for the fundamentally justified spread level. The deviation between market and model spreads is subsequently analyzed within the framework of a dynamic panel regression. Besides firm-specific, regional and rating differences, the analysis controls for factors which have been mentioned in prior literature to influence CDS market spreads but are not incorporated in the models. Most factors are confirmed but the results additionally point to the requirement to account for market spread exaggerations. Other studies have not been able to detect and incorporate those due to the often limited time horizon and the absence of significant market shocks as for example the events of the subprime crisis. Furthermore, public credit derivative indices have been initiated only after the emergence of the conjectured bubble and therefore only show the surge of spreads since mid-2007.

The results provide suggestions for researchers as well as practitioners. They show that portfolio positions have to be evaluated constantly and related to their truly fundamental value. The strong growth in market volume of synthetic structured credit derivatives together with significantly declining CDS spreads resulted in strong deviations between balance sheet and market-reflected credit risk of the underlying obligors and could have provided a signal for mispricing. The decline in spreads was further amplified by the aspect of a rational bubble implying that investors would sell protection with the expectation of spreads to further decrease although already at low levels. On the other hand, the results also show that the present structural pricing models do not capture all important factors on CDS and therefore do not always replicate the fundamentally verified level. They clearly suggest the importance of forward-looking macro-indicators as well as liquidity measures and the incorporation of implied volatilities. As the market continues to grow further model advancements have to be developed and evaluated empirically maintaining CDS a vivid area of research as well as investment.

Appendix

The CDS Pricing Models - Preliminaries

For all models, let V_t, S_t, D_t, and K_t denote the asset value, the market value of equity, the amount of total liabilities, and the default barrier of the associated firm at time t divided by the number of shares outstanding, respectively. Correspondingly, σ_V and σ_S denote the annualized asset and equity volatilities, r the risk-free interest rate, and R the recovery rate on the senior subordinated debt underlying the CDS initiated at time $t = 0$ with maturity T.

The CreditGrades Model (2002)

Corresponding to Collin-Dufresne and Goldstein (2001), V_t is assumed to follow a geometric Brownian motion with zero drift under the risk-neutral measure, namely

$$dV_t/V_t = \sigma_V dW_t$$

where W_t is a Wiener process. Within this approach, the default barrier is defined by $K_t = L \cdot D_t$, where L is a log-normal random variable with $\mathrm{E}(L) = \bar{L}$ and $\mathrm{Var}(\ln L) = \sigma_L^2$ revealed at the time of default. The current probability $q(t)$ that the asset value does not reach the default barrier before $t \in [0;\ T]$ is approximated by

$$q(t) = \Phi(a_t^+) - d \cdot \Phi(a_t^-),$$

where $\Phi(..)$ is the cumulative distribution function of the standard normal distribution and

$$a_t^{\pm} = -A_t/2 \pm \ln d/A_t,$$

$$A_t^2 = \sigma_V^2 t + \sigma_L^2,$$

and

$$d = \frac{(S_0 + \bar{L}D_0)\exp(\sigma_L^2)}{\bar{L}D_0}.$$

The value of the current credit default swap premium $c(0,T)$ initiated at time $t = 0$ with maturity T is expressed as

$$c(0,T) = r(1-R)\frac{1 - q(0) + H(T)}{q(0) - \exp(-rT)q(T) - H(T)}$$

where

$$H(T) = \exp(r\xi)\big(G(T+\xi) - G(\xi)\big),$$

$$G(T) = d^{\omega+1/2}\Phi(g_T^-) + d^{-\omega+1/2}\Phi(g_{\mathrm{T}}^+),$$

$$g_T^\pm = \frac{-\ln d \pm \omega\sigma_V^2 T}{\sigma_V\sqrt{T}},$$

$$\xi = \sigma_L^2/\sigma_V^2,$$

and

$$\omega^2 = 1/4 + 2\,r/\sigma_V^2.$$

The asset volatility σ_V is approximated according to Finger et al. (2002) as

$$\sigma_V = \sigma_S \frac{S_t}{S_t + \bar{L}D_t},$$

whereas σ_S is estimated from historical data resulting in a time-series of asset volatilities.

The Model of Leland and Toft (1996)

In this model, the asset value is assumed to follow a geometric Brownian motion under the risk-neutral measure, i.e.

$$dV_t/V_t = (r-\beta)dt + \sigma_V dW_t$$

where β denotes the asset payout rate which is approximated for each sampling point using $\beta = (div_t + ie_t)/(S_t + D_t)$ with div_t and ie_t denoting the dividend and the total interest expenses per share at time t.

Following Ericsson, Reneby and Wang (2005), the total outstanding debt principal is assumed to correspond to D_t and the average coupon paid out to all debt holders equals the risk-free interest rate, i.e. $C = rD_t$. Using these assumptions, the market value of equity is rewritten as

$$S(V_t, \sigma_V) = V_t + \delta D_t(1 - (V_t/K_t)^{-a-z}) - \alpha K_t (V_t/K_t)^{-a-z}$$

$$-D_t - \big((1-\alpha)K_t - D_t\big)J(Y),$$

where

$$J(Y) = \frac{-k^{+}\Phi(j_Y^{-})j_Y^{-} + k^{-}\Phi(j_Y^{+})j_Y^{+}}{z\sigma_V\sqrt{Y}},$$

$$k^{\pm} = (V_t/K_t)^{-a\pm z},$$

$$j_Y^{\pm} = \frac{-\ln(V_t/K_t) \pm z\sigma_V^2 Y}{\sigma_V\sqrt{Y}},$$

$$a = \frac{r - \beta - \sigma_V^2/2}{\sigma_V^2},$$

and

$$z^2 = a^2 + 2\,r/\sigma_V^2.$$

Let $\phi(..)$ denote the standard normal density function. Using the assumptions, the default barrier given in Leland and Toft (1996) can be rewritten as

$$K_t = D_t \frac{-B - \delta(a+z)}{1 + \alpha(a+z) - (1-\alpha)B}$$

where

$$B = -\left(2z + \frac{2}{z\sigma_V^2 Y}\right)\Phi\big(z\sigma_V\sqrt{Y}\big) - \frac{2}{\sigma_V Y}\phi\big(z\sigma_V\sqrt{Y}\big) + (z-a) + \frac{1}{z\sigma_V^2 Y}.$$

To capture the unobserved asset values and volatilities, the following relationship is solved numerically

$$S(V_t, \sigma_V) = S_t \tag{1}$$

$$\sigma_S = \frac{\partial S(V_t,\sigma_V)}{\partial V_t}\frac{V_t}{S_t}\sigma_V \tag{2}$$

For this purpose, $S_t + D_t$ are used as initial value for V_t to obtain the corresponding implied volatility σ_V from (1) which, in the following step, is used to calculate V_t from (2) by means of the historical estimate of σ_S for the given firm. This procedure is repeated for each observation until the values of σ_V converge, resulting in a time-series of asset values and volatilities. The current survival probability $q(t)$ is given by

$$q(t) = 1 - F(t),$$

where

$$F(t) = \Phi(h_t^-) + (V_0/K_0)^{-2a}\Phi(h_t^+),$$

and

$$h_t^{\pm} = \frac{-\ln(V_0/K_0) \pm a\sigma_V^2 t}{\sigma_V\sqrt{t}}.$$

The value of the current credit default swap premium $c(0,T)$ is then expressed as

$$c(0,T) = r(1-R)\frac{Q(T)}{1-\exp(-rT)\,q(T) - Q(T)},$$

with

$$Q(T) = k^+\Phi(j_T^-) + k^-\Phi(j_T^+).$$

The Model of Zhou (2001)

Let X_t denote the asset value of the associated firm at time t relative to the default barrier, i.e. $X_t = V_t/K_t$ and assume $V_t = S_t + D_t$ and $K_t = D_t$. In Zhou (2001) X_t follows a jump-diffusion process given by

$$dX_t/X_t = (\mu - \lambda\nu)dt + \sigma dW_t + (\Pi - 1)dY_t$$

where μ is a drift and σ a volatility parameter, Y_t is a homogenous Poisson process with intensity λ, and Π is the log-normal jump-amplitude with $\ln\Pi \sim \mathrm{N}(\mu_\Pi;\ \sigma_\Pi^2)$. The parameter ν satisfies $\nu = \mathrm{E}(\Pi - 1) = \exp(\mu_\Pi + \sigma_\Pi^2/2) - 1$.

W_t, Y_t, and Π are assumed to be independent. Applying Ito's lemma to $x_t = \ln X_t$ yields

$$dx_t = (\mu - \sigma^2/2 - \lambda\nu)dt + \sigma dW_t + \ln\Pi\, dY_t. \tag{3}$$

Let $\theta = (\mu, \sigma, \lambda, \mu_{\Pi}, \sigma_{\Pi})'$ denote the parameter vector to be estimated numerically from an observed sample of x_t with n observations. Since, as mentioned in Wong (2006), the probability of more than one jump arriving within two sampling-points is of secondary order, the corresponding likelihood function $L(\theta)$ is given by

$$L(\theta) = \prod_{i=2}^{n} g(x_i | x_{i-1}, \theta),$$

where $g(x_i | x_{i-1}, \theta)$ is the density of x_i conditioning on x_{i-1} which is approximated via

$$g(x_i | x_{i-1}, \theta) = (1 - \lambda \Delta t) f_X(x_i | x_{i-1}, \theta) + \lambda \Delta t f_{XY}(x_i | x_{i-1}, \theta),$$

$$f_X(x_i | x_{i-1}, \theta) = \frac{1}{\sqrt{2\pi\sigma^2 \Delta t}} \exp\left(-\frac{(x_i - x_{i-1} - (\mu - \sigma^2/2 - \lambda\nu)\Delta t)^2}{2\sigma^2 \Delta t}\right),$$

$$f_{XY}(x_i | x_{i-1}, \theta) = \int_{-\infty}^{+\infty} f_X(x_i - y | x_{i-1}, \theta) f_Y(y) dy,$$

and

$$f_Y(y) = \frac{1}{\sqrt{2\pi\sigma_{\Pi}^2}} \exp\left(\frac{(y - \mu_{\Pi})^2}{2\sigma_{\Pi}^2}\right).$$

The subsequent Monte Carlo approach incorporates the estimates of θ and is based on simulated samples of the discrete time version of x_t given in (3) under the risk-neutral measure. The simulated process $\tilde{x}_t$ is expressed as

$$\tilde{x}_i - \tilde{x}_{i-1} = (r - \sigma^2/2 - \lambda\nu) T/m + \sigma\sqrt{T/m}\, \varepsilon_i + \ln \Pi\, (Y_i - Y_{i-1}), \quad (4)$$

where m is the size of the simulated sample, $\tilde{x}_0$ is the starting value, ε_i is a standard normal white noise with $i = 0, \dots, m$, and $\mathrm{P}(Y_i - Y_{i-1} = 0) = 1 - \lambda T/m$, or $\mathrm{P}(Y_i - Y_{i-1} = 1) = \lambda T/m$.

The simulated samples are generated for each observation of x_t using the current observations as starting values and M replications, respectively. Let $\tilde{x}_{i,j}$ denote the i-th simulated observation in the j-th sample of the process given in (4) and let τ_j denote a hitting time satisfying $\tau_j = \min\{i | \tilde{x}_{i,j} \leq 0\}$, where $i = 1, \dots, m$ and $j = 1, \dots, M$. The current credit default swap premium $c(0,T)$ is then calculated by

$$c(0,T) = -T^{-1} \ln \left(1 - \sum_{j=1}^{M} z_j / M \right),$$

where

$$z_j = \begin{cases} ((1-R)\exp\left(\tilde{x}_{\tau_j, j}\right) & \text{if} \{\tau_j\} \neq \emptyset, \\ 0 & \text{otherwise.} \end{cases}$$

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