International Journal of Economics and Finance; Vol. 5, No. 4; 2013
ISSN 1916-971X E-ISSN 1916-9728
Published by Canadian Center of Science and Education

When Risks and Market Inefficiency Shake Hands – An Empirical Analysis of Financial CDS

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Received: February 1, 2013 Accepted: March 4, 2013 Online Published: March 18, 2013

doi:10.5539/ijef.v5n4p39 URL: http://dx.doi.org/10.5539/ijef.v5n4p39

Abstract

This paper examines the relation between absolute CDS premium and the market efficiency of financial institutions. We test the random-walk hypothesis on 3-years CDS data set using: Q-statistics portmanteau tests by Box and Pierce, variance ratio tests by Lo and MacKinlay, variance ratio tests using ranks and signs by Wright, and wild bootstrapping variance ratio tests by Kim. We find that CDSs with the highest means and the highest standard deviations tend to fail the random-walk hypothesis. These CDSs have the highest potential to trade in an inefficient market with the highst potential for speculation and market manipulation (i.e. by hedge funds). This inefficiency negates the original function of hedging. To reconstitute the function of hedging and to overcome a CDS market that is driven by speculation our research concludes that it is necessary to adopt further regulations for the CDS market.

Keywords: Credit Default Swaps, credit derivatives, market efficiency, random-walk-hypothesis

1. Introduction

Credit Default Swaps (CDS) are the most common credit derivatives and the most important risk management tools for credit risks. CDSs allow investors to insure their portfolios against pre-defined credit events. The functionality is as follows: The protection buyer makes periodic payments (in the amount of the CDS spread) and the protection seller offers to compensate the protection buyer (also periodically) if a pre-defined credit event occurs. If no credit event occurs, the CDS contract terminates without any compensation payments. The market for credit derivatives is a global, over-the-counter financial market which started in the mid-1990s and is dominated by banks, insurers, reinsurers, hedge funds, investment funds and large non-financial companies. Furthermore it is a transparent market where every market participant has the possibility to get all necessary information via information systems (e.g. Bloomberg). Most contracts are regulated by the International Swaps and Derivatives Association (ISDA). Therefore, it is to be expected that the CDS market should be an efficient market in the definition of Fama. The market reached its peak, according to the International Swaps and Derivatives Association (ISDA (2010)), right before the beginning of the financial crisis at the end of 2007 with a notional value around 62.2 Trillion USD. That value has declined continuously since the outbreak of the financial crisis. The latest estimates by the ISDA (2010) are for a notional value up to 26.3 trillion USD in 2010. Nevertheless CDS still represent a relevant factor within the financial market: (i) CDS spreads became an economic indicator for corporate credit liability. Therefore CDS spreads have a direct impact on corporate debt ratings and credit rates. (ii) For countries, CDS became the most important factor for the emission price of bonds. Corporate credit liability and sovereign debt prices play a large role in the economy. Thus, CDS spreads greatly influence our economic welfare. In this analysis we concentrate our research on CDS for banks. Investors pay credit spreads to protect them against the risk of default by the bank. In 2011/2012 CDS spreads for banks are at historic highs. This is due to the fear of contagion of the European debt crisis, disappointing earnings trends, expectations of rating downgrades and unsettling comments by politicians and international institutions. The collapse of Lehman Brothers has caused the CDS markets to become a target for speculators. The near collapse of Greece has further increased speculation. For investors hedging portfolios with CDS it is important to know if the increase in speculative activity affects market efficiency. Therefore our essay focuses on the problem of weak-form market efficiency of CDS markets. We check market efficiency by using the random-walk

hypothesis. The data we use in our research is 3-years of daily and weekly CDSs on 30 international banks. We test the random-walk hypothesis by using the latest test statistics (Box & Pierce Q-statistics, variance ratio tests by Lo and MacKinlay, variance ratio tests using ranks and signs by Wright and wild bootstrapping variance ratio tests by Kim). The main interest of our research is the relation between CDS premiums and market efficiency. We support our findings with the use of the scoring model framework.

2. Literature Review

In general, contemporary research of the CDS market consists of 2 different streams: informational efficiency in the CDS market and regulatory issues of CDS as a financial instrument. There is no research analyzing the random-walk hypothesis of CDS markets.

On the first stream, one of the findings in the empirical research of Ancharya and Johnson (2007) concluded that there is an information flow from the CDS market to the equity markets. The analysis of Jenkins et al. (2011) verified the informational efficiency of the CDS market. This is shown by the relationship between movements in subsequent CDS prices and previously announced accounting information. Hull et al. (2004) and Norden and Weber (2004) analyzed the response of stock and CDS markets to rating announcements. The empirical findings of Norden and Weber (2004) showed that the CDS and stock market anticipate rating downgrades. Anticipation starts approximately 60-90 days before the announcement day. Further findings came to the conclusion that stock and CDS markets also reviews for downgrade, and that the CDS market tends to react more quickly. Callen et al. (2009) evaluated the impact of earnings on credit risks in the CDS market. They found that a 1% increase in earnings reduces the CDS premium by 5% to 9%. Zhang (2009) showed the plausibility of the existence of informational efficiency by testing CDS prices on a variety of credit events. Furthermore his analysis showed that CDSs in comparison to stocks have more frequent large price changes. Within an empirical analysis Blanco et al. (2005) tested the theoretical equivalence of CDS prices and Investment-Grade bonds. Their results showed that first CDS prices are substantially higher than credit spreads and second the CDS market lead the bond market in the price discovery process for credit risks. Coudert and Gex (2010) analyzed the link between CDSs and bonds. They came to the conclusion that the CDS market (for corporations) leads the bond market in the price discovery process. Zhu (2006) identified that in the short run the derivatives market moves ahead of the bond market in price discovery, while in the long run credit risks are equally priced. These results imply that the CDS market needs less time to process new information.

On the second stream, Avellanda and Cont (2010) first gave an overview of existing forms of transparency in CDS markets. Second, in speaking about the importance of evaluating costs and benefits they introduced further possibilities of increasing transparency for CDSs. Duquerroy et al. (2009) showed an overview of the CDS market and pointed out challenges for regulators to improve transparency. Cont (2010) disclosed the impact of CDSs on financial stability. She argued that an unregulated market opens the possibility of contagion (especially in the case of counterparty risk) and systematic risks. Further she introduced central clearing as a method to reduce counterparty risks.

3. Data and Methodology

3.1 Data

Our CDS data collection consists of a set of CDS spreads of international banks provided by Bloomberg. Because CDSs are traded in the OTC market, mainly in London and New York, gaps in the data collection are unavoidable. CDS prices delivered by Bloomberg are intraday prices averaged to one daily price that represents the arithmetic mean of prices received by the agency during the previous 24 hours. We adjusted the data sample for weekends and public holidays. We considered daily observations on 3-year CDS spreads from December 14th 2007 to August 22nd 2011 for the analysis. As the data set spans the period of nearly 4 years our data has an adequate sample period to gain statistically valid evidence to address our problem statement. Every CDS spread that gets used in our sample must meet the following 2 filter criteria: (i) the observed entity has to be a system-relevant bank in its country; (ii) the entity provides a reasonable number of observations (minimum 250), as the number of observations is especially important to achieve significance in the accomplished statistical tests. The filtering yields us 30 entities (22 European banks, 6 American banks and 2 Asian-Pacific banks) and 26236 observations on CDS spreads. Additionally, in order to strengthen the comparability, we build out of the data of the daily observations a data set of weekly observations which still consists of 5373 observations. To get a better impression and for preparing the data for the test statistics we make use of descriptive statistics. Table 1 summarizes daily observations on the logarithm data set of the CDS spreads. Table 2 does the same for weekly observations. As for the necessary test statistic, we test the sample set for normality using Kolmogorov-Smirnov and Jarque-Bera test. We strongly reject the normality assumption for both the daily and weekly data set.

Table 1. Descriptive statistics (daily)

	Bank of America	Barclays	BayernLB	BNP	Citigroup	Commerzbank	Credit Mutual	Credit Suisse	Deutsche Bank	Erste Bank
Mean	0,002529214	0,002101716	0,001440076	0,002493941	0,0014678	0,002260265	0,000213446	0,001489854	0,001762979	0,000766301
Median	0	0	0	0	0	0	0	0	0	0
Maximum	130,8546936	104,4972341	101,9509725	66,68574194	189,5755951	89,0086553	82,85414602	88,59916585	85,01785195	165,0807336
Minimum	-0,476924072	-0,387116042	-0,267338082	-0,347401307	-0,819920497	-0,312374648	-0,255350435	-0,387115969	-0,420001423	-0,473287704
Std. Dev.	0,069149661	0,06476644	0,044569388	0,068371301	0,075981284	0,06659043	0,030826097	0,063548292	0,065789446	0,0423009
Skewness	0,1219924	-0,412609	0,999305	-0,218194	-1,487039	0,7046877	3,485156	-0,2703211	-0,01278158	-0,06530696
Kurtosis	11,65283	6,258725	17,98842	3,871748	31,20216	10,08363	82,71571	8,288042	7,101699	39,31944
Kolmogorov-Smirnov	0,4273	0,4279	0,4429	0,4246	0,4326	0,426	0,4613	0,4288	0,427	0,4522
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Jarque-Bera	5298,074	1554,253	12775,53	592,0539	38314,38	4042,972	177142,6	2690,374	1966,957	45865,73
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Observations	936	936	936	936	936	936	617	936	936	712

	Goldman Sachs	HSBC	HSH	ING	JP Morgan	LBBW	LBHT	Macquarie	Merill Lynch	Morgan Stanley
Mean	0,001357774	0,001249372	0,001014051	0,001766561	0,001166712	0,001726046	0,000573336	3,60072E-05	0,001165887	0,00126043
Median	0	0	0	0	0	0	0	0	0	0
Maximum	148,618876	66,29828239	192,5398728	86,18421978	76,82485471	117,2708306	108,8114504	226,7099471	195,9603947	218,9469781
Minimum	-0,825447583	-0,328504067	-0,312984255	-0,371563556	-0,586529579	-0,672093771	-0,484323683	-1,488077055	-0,775211761	-1,143357132
Std. Dev.	0,070618665	0,05649592	0,04162417	0,059311795	0,073335649	0,050338856	0,037080798	0,078489125	0,065584943	0,073468307
Skewness	-0,1779251	0,4209303	-0,2363533	-0,1177319	-0,2412468	-0,4994438	0,1300032	-7,223284	-1,078299	-3,021617
Kurtosis	36,43218	12,67751	12,04204	7,957335	13,04762	64,75417	63,83512	155,3044	28,75652	77,59216
Kolmogorov-Smirnov	0,4331	0,4358	0,4389	0,4301	0,4251	0,4461	0,4525	0,44	0,4335	0,4402
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Jarque-Bera	51769,77	6295,691	5664,129	2471,61	6648,455	141550,9	137530,9	896087	32431,94	236225,5
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Observations	936	936	936	936	936	810	810	884	936	936

	Natixis	Nomura	NordLB	Rabobank	RBS	Santander	Societe General	UBS	Unicredit	WestLB
Mean	0,001025494	0,000846824	0,001711558	0,00140459	0,001136529	0,002425742	0,002744081	0,001674382	0,001930772	0,001674264
Median	0	0	0	0	0	0	0	0	0	0
Maximum	175,9085715	153,2917766	104,2941655	68,71455753	140,9852086	122,351839	91,13524029	110,2081566	85,44125753	128,4422633
Minimum	-0,409784769	-0,315081047	-0,472253349	-0,496814887	-0,546968287	-0,440654556	-0,427894957	-0,414433778	-0,174807485	-0,336472237
Std. Dev.	0,04955574	0,04706296	0,048378066	0,060118647	0,065110181	0,066838553	0,06210175	0,061585957	0,040438355	0,054220621
Skewness	0,9370441	0,4235043	0,9162107	-0,8851651	0,6236538	-0,3587463	0,1256015	0,5745485	0,388656	1,58052
Kurtosis	35,82997	12,98046	31,82812	11,97985	33,96301	6,651318	5,22655	17,04353	5,983109	20,98675
Kolmogorov-Smirnov	0,4418	0,4364	0,4398	0,4288	0,4381	0,4242	0,4306	0,4312	0,4491	0,4358
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Jarque-Bera	43714,52	6176,155	34303,07	5719,386	42544,05	1745,438	1067,817	11380,29	451,9891	17567
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Observations	815	876	810	936	884	936	936	936	298	936

Table 2. Descriptive statistics (weekly)

	Bank of America	Barclays	BayernLB	BNP	Citigroup	Commerzbank	Credit Mutual	Credit Suisse	Deutsche Bank	Erste Bank
Mean	0,010944743	0,015813539	0,003287209	0,014044116	0,011562085	0,006876808	0,000914789	0,008302769	0,011087497	0,001519884
Median	0,013927933	0,026547407	0	0,013832011	0,012647394	0,003669158	0	0,010510174	0,010696271	0
Maximum	0,416514944	0,597660753	0,300648261	0,530749654	0,879745215	0,468725293	0,435573995	0,489014327	0,539276104	0,435318071
Minimum	-0,534520035	-0,4283046	-0,312434439	-0,570544858	-0,694757354	-0,508497334	-0,255248924	-0,487547939	-0,526093096	-0,521296924
Std. Dev.	0,141552675	0,135374283	0,080598074	0,146991121	0,15864929	0,135489964	0,061271565	0,126570927	0,140690419	0,097985232
Skewness	-0,4165143	0,1802407	-0,5734668	-0,05550764	0,2298433	-0,2737894	1,961857	-0,2981317	-0,1788083	-0,0427315
Kurtosis	1,873618	2,271332	3,192385	1,554018	6,599131	2,389623	22,83348	2,393754	1,825576	7,551322
Kolmogorov-Smirnov	0,376	0,3869	0,4265	0,3739	0,3731	0,3908	0,4374	0,3906	0,3783	0,4242
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Jarque-Bera	33,6351	42,3112	92,0542	19,4184	350,0787	48,0811	2818,006	4,87E+01	27,6849	344,5549
Probability	4,97E-08	6,49E-10	< 2.2E-16	6,07E-05	< 2.2E-16	3,63E-11	< 2.2E-16	2,68E-11	9,73E-07	< 2.2E-16
Observations	192	192	192	192	192	192	126	192	192	145

	Goldman Sachs	HSBC	HSH	ING	JP Morgan	LBBW	LBHT	Macquarie	Merill Lynch	Morgan Stanley
Mean	0,005645198	0,006365493	0,005353957	0,012626222	0,008707367	0,002656534	0,0001153	0,00265508	0,008111803	0,00801411
Median	0,009678454	8,10929E-05	0	0,013889476	0,000388939	0	0	0	1,67055E-06	0,007549954
Maximum	0,588157556	0,44857077	0,227997054	0,386636082	0,521284373	0,251314428	0,384738978	0,732678019	0,44510429	0,790040001
Minimum	-0,654822066	-0,529402009	-0,259323208	-0,478395287	-0,533898971	-0,672093771	-0,484323683	-1,32985305	-0,749236275	-0,882630869
Std. Dev.	0,137045785	0,115959332	0,070003109	0,123022403	0,150440513	0,081385585	0,077310067	0,1689237	0,139149837	0,147956834
Skewness	-0,4247358	-0,6209675	-0,1261076	-0,6997216	0,000926049	-3,206158	-0,2668123	-2,457785	-0,6628314	0,007841373
Kurtosis	4,273315	4,234022	2,246398	2,509119	2,050676	28,51705	14,55241	24,67095	4,748157	12,18515
Kolmogorov-Smirnov	0,3794	0,4024	0,4189	0,3876	0,3703	0,4309	0,4273	0,3941	0,3741	0,3829
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Jarque-Bera	151,8626	155,7548	40,8793	66,033	33,6449	5873,585	1457,894	4772,507	194,419	1187,826
Probability	< 2.2E-16	< 2.2E-16	1,33E-09	4,55E-15	4,94E-08	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
Observations	192	192	192	192	192	165	165	181	192	192

	Natixis	Nomura	NordLB	Rabobank	RBS	Santander	Societe General	UBS	Unicredit	WestLB
Mean	0,003473429	0,000451241	0,005391955	0,007141626	0,011113105	0,014604382	0,016426955	0,01032811	0,004156152	0,011285155
Median	0	0,062557972	0	0,016297805	0,009478744	0,002131724	0,012412506	0,008700503	0	3,71181E-05
Maximum	0,274901444	0,39111766	0,472253349	0,394024503	0,626455806	0,515938456	0,602569118	0,35829964	0,307606695	0,54690168
Minimum	-0,487836106	-0,478035801	-0,472253349	-0,523248144	-0,626455806	-0,474312926	-0,474665642	-0,627300615	-0,228080725	-0,63111179
Std. Dev.	0,099103765	0,092915831	0,083722091	0,133215985	0,126907085	0,144985655	0,137246006	0,133412585	0,093795719	0,117309987
Skewness	-0,9427466	-0,1008396	0,3009053	-0,8535683	-0,4671648	0,06538897	0,2639506	-0,9029849	0,419681	-0,6123122
Kurtosis	4,425717	5,777642	12,31166	2,703386	7,566127	1,929067	2,591628	4,331597	0,9684752	7,011917
Kolmogorov-Smirnov	0,3975	0,4169	0,4246	0,3846	0,3937	0,3729	0,3915	0,3924	0,4197	0,3954
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	1,32E-09	< 2.2E-16
Jarque-Bera	160,0659	249,2711	1044,582	81,7809	438,316	29,9072	55,9617	176,1941	4,1062	405,3335
Probability	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16	3,20E-07	7,05E-13	< 2.2E-16	0,1283	< 2.2E-16
Observations	166	179	165	192	181	192	192	192	60	192

3.2 The Random-Walk Hypothesis

Fama (1970) defined an efficient market as one in which prices reflect all available information. In this case the prices reflect even hidden or insider information. If there is no additional data for the investors available, nobody has the ability to take advantage on the market in predicting prices. The market tends to have a semi-strong efficiency if prices already reflected all public information i.e. companies' annual reports. The weak-form market efficiency refers to the predictability in time series of prices on the basis of past information. Samuelson (1965) demonstrated that the price-generating process of a weak-form efficient market should only be affected by the arrival of new information. New information is assumed to appear at random, so prices should follow a random-walk. Price changes are not dependent on each other. A simple random-walk process can be defined as:

$$P_t = P_{t-1} + u_t \tag{1}$$

where

P_t = Price at time t

u_t = error term for time t

As Campbell et al. (1997) stated, there are three different versions of the random-walk hypothesis, each of them being slightly more stringent. The strongest assumption implies that all error terms u_t are independent and identically distributed (i.i.d.):

$$u_t \sim \text{IID}(0, \sigma^2) \tag{2}$$

This assumption implies that absolutely no information on price changes can be obtained from the past. We applied homoscedastic variance ratio tests by Lo and MacKinlay and nonparametric variance ratio tests based on ranks by Wright to test the strong version of random-walk hypothesis.

The semi-strong form implies that the distribution of the arrival of news can change over time, but it is still independent:

$$u_t \sim \text{indep}(0, \sigma^2) \tag{3}$$

This form is very difficult to test because every single might come from a totally different distribution. We did not test the semi-strong version of the random-walk hypothesis.

The weak form is based on the correlation of the error terms and implies:

$$\text{cov}(u_t, u_{t-k}) = 0 \tag{4}$$

This version is especially important, as heteroscedasticity may be a reason for rejecting the strong version of the random-walk hypothesis.

We applied Q-statistics portmanteau tests, heteroscedastic variance ratio tests by Lo and MacKinlay, nonparametric variance ratio tests based on signs by Wright and wild bootstrapping variance ratio tests by Kim to test the weak version of the random-walk hypothesis.

3.3 Box-Pierce Q-Statistics

The Q-statistics portmanteau test developed by Box and Pierce (1970) is a possible method for testing a time series for white noise, an uncorrelated sequence of errors, which is also a definition for a weak-form random-walk. We used the relative future price change as a sequence for the sample basis. The Box-Pierce Q-Statistics are calculated as a linear operation of various squared autocorrelations with different time lags, all weighted equally. It can be defined as:

$$Q_m = n \sum_{k=1}^{m} r_k^2 \tag{5}$$

where

Q_m = Box-Pierce Q-statistic for *m* time lags

m = number of coefficients

n = number of observations

r_k = autocorrelation coefficient for time lag *k*

To test the validity of the random-walk hypothesis, the Q-statistic is computed for various values of *m*. For large sample sizes *n*, Campbell et al. (1997) showed that the sample autocorrelation coefficients are asymptotically independent and normally distributed.

$$\sqrt{n}r_k \sim \mathrm{N}(0,1) \tag{6}$$

Thus if the price change series is Gaussian distributed, then the Q-statistic is distributed like the sum of squares of *m* Gaussian random variables. So this statistic is asymptotically distributed as the chi-square distribution with *m* degrees of freedom.

The null hypothesis can be defined as:

$$H_0 : Q_m \sim \chi_m^2 \tag{7}$$

Q-statistics points out any deviation from the null hypothesis of no autocorrelation in any direction, and at all considered time lags depending on the value of *m*. The selection of *m* is critical for the statistical power of the test, as too small values of *m* would disregard possible higher order autocorrelation, and too high values of *m* would reduce statistical significance. We tried to avoid this problem by calculating all Q-statistics for *m* = 1 to *m* = 10, for both daily and weekly observations.

3.4 Variance Ratio Tests by Lo and MacKinlay

The variance ratio tests by Lo and MacKinlay (1988) were first proposed to test for a random-walk in case of homoscedasticity and later extended to the more general case of an uncorrelated random-walk in case of heteroscedasticity. This test utilises data sampled at various frequencies. Lo and MacKinlay (1989) demonstrated that variance ratio tests are statistically more powerful than the Box-Pierce Q-statistics. As an important property of a random-walk, the variance of its increments is linear in the observed period. Specifically, the variance estimated from the q-periods returns should be *q* times as large as the variance estimated from one-period returns, or:

$$\frac{Var\left(r^q{}_t\right)}{Var\left(r_t\right)} = q \tag{8}$$

where

$r^q{}_t$ = Returns of a sample *t* for a the period with a length of *q*

r_t = Returns of a sample *t* with one-period length

The variance ratio *VR(q)* can be defined as:

$$VR(q) = \frac{Var\left(r_t^q\right)}{qVar\left(r_t\right)} \tag{9}$$

The null hypothesis is therefore:

$$H_0 : VR(q) = 1 \tag{10}$$

Lo and MacKinlay derived asymptotic standard normal test statistics for their variance ratios. We used two different test statistics: *z(q)* in case of homoscedasticity, and *z*(q)* in case of heteroscedasticity. The first statistic *z(q)* assumes an i.i.d. error term. The standard normal *z(q)* test statistic can be computed as:

$$z(q) = \frac{VR(q)-1}{\sqrt{\phi(q)}} \approx N(0,1) \tag{11}$$

where

$$\phi(q) = \frac{2(2q-1)(q-1)}{3q(nq)} \tag{12}$$

The heteroscedastic test statistic *z*(q)* allowed us to relax the requirements of i.i.d. increments. Despite the presence of heteroscedasticity, the test statistic *z*(q)* is still asymptotically standard normal in case of a random-walk. It can be defined as:

$$z^*(q) = \frac{VR(q)-1}{\sqrt{\phi^*(q)}} \approx N(0,1) \tag{13}$$

where

$$\phi^*(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q} \right]^2 \hat{\delta}(j) \tag{14}$$

and

$$\hat{\delta}(j) = \frac{\sum_{k=j+1}^{nq} (P_k - P_{k-1} - \hat{\mu})^2 (P_{k-j} - P_{k-j-1} - \hat{\mu})^2}{\left[\sum_{k=1}^{nq} (P_k - P_{k-1} - \hat{\mu})^2 \right]^2} \tag{15}$$

where

$\hat{\mu}$ = Average return

We used both homoscedastic and heteroscedastic test statistics for aggregation values q of 2, 4, 8 and 16.

3.5 Variance Ratio Tests Using Ranks and Signs by Wright

Wright (2000) introduced alternative variance ratio tests based on ranks and signs. He showed that for some processes his nonparametric variance ratio tests are performing better in rejecting violations of the random-walk hypothesis than the tests recommended by Lo and MacKinlay. He explained the outperformance of ranks- and signs-based tests by the mention of two potential advantages. First, his tests often allow for computing the exact distribution. As it is not necessary to appeal to any asymptotic approximation, size distortions can be neglected. Second, if the sample data is highly nonnormal, tests based on ranks and signs may be more powerful than other variance ratio tests. Formally for the ranks-based tests, let $r(r_t)$ be the rank of the difference of the futures prices r_t among $r_1, r_2, ...r_t$. Then, r_{1t} and r_{2t} are the ranks of the futures price differences, defined as:

$$r_{1t} = \frac{\left(r\left(r_t - \frac{T+1}{2} \right) \right)}{\sqrt{\frac{(T-1)(T+1)}{12}}} \tag{16}$$

$$r_{2t} = \Phi^{-1}\left(\frac{r(r_t)}{T+1} \right) \tag{17}$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function.

The series r_{1t} is a simple linear transformation of the ranks, standardised to have a sample mean 0 and a sample variance 1. The series r_{2t}, known as the inverse normal or van der Warden score, has a sample mean 0 and a sample variance approximately equal to 1. The rank series r_{1t} and r_{2t} substitute the difference in futures prices $(P_t - P_{t-q})$ in the definition of the variance ratio test statistic by Lo and MacKinlay z(q) in equation (11), which is written as R_1 and R_2 :

$$R_1 = \left(\frac{\frac{1}{Tq} \sum_{t=q+1}^{T} (r_{1t} + r_{1t-1} ... + r_{1t-q})}{\frac{1}{T} \sum_{t=1}^{T} r_{1t}^2} - 1 \right) * \frac{1}{\sqrt{\phi(q)}} \tag{18}$$

$$R_2 = \left(\frac{\frac{1}{Tq} \sum_{t=q+1}^{T} (r_{2t} + r_{2t-1} ... + r_{2t-q})}{\frac{1}{T} \sum_{t=1}^{T} r_{2t}^2} - 1 \right) * \frac{1}{\sqrt{\phi(q)}} \tag{19}$$

where $\phi(q)$ is defined in equation (12).

Wright (2000) demonstrated that under the assumption that the rank $r(r_t)$ is an unbiased, random permutation of the numbers $1,2,...,T$, the test statistics' distribution can be provided. So the exact sampling distribution of R_1 and R_2 may easily be simulated to an arbitrary degree of accuracy, for a given choice of T and q. Therefore, the distribution does not suffer from disturbance parameters and the test can be used to construct a test with exact power.

By using the signs of the differences instead of the ranks, it may be possible to apply a variance ratio test that is exact in case of conditional heteroscedasticity. Formally, for a time series r_t, let $u(r_t,k)=1(r_t>k)-0.5$. Thus $u(r_t,0)$ is 0.5 if r_t is positive and -0.5 otherwise. Let $s_t=2u(r_t,0)=2u(\varepsilon_t,0)$. Clearly, s_t is an i.i.d. series with zero mean and variance equal to one. Each s_t is equal to 1 with a probability 0.5 and is equal to -1 otherwise. The test statistic based on signs S_1 is given by:

$$S_1=\left(\frac{\frac{1}{Tq}\sum_{t=q+1}^{T}(s_t+s_{t-1}...+s_{t-q})^2}{\frac{1}{T}\sum_{t=1}^{T}s_t^2}-1\right)*\frac{1}{\sqrt{\phi(q)}} \tag{20}$$

In Monte Carlo experiments and empirical tests, Wright showed that this test could be exact and more powerful than other variance ratio tests under both homoscedastic and heteroscedastic conditions.

3.6 Wild Bootstrapping Variance Ratio Tests by Kim

Kim (2006) proposed variance ratio tests based on wild bootstrapping – a re-sampling method that approximates the sampling distribution of the test statistic. The main advantage of this finite sample test is the fact that it does not rely on asymptotic approximations. Therefore, it is robust to nonnormality. Wu (1986) and Mammen (1993) demonstrated that wild bootstrapping should be a natural choice in case of conditional and unconditional heteroscedasticity. The test is based on a Chow and Denning (1992) joint version of the Lo and MacKinlay test statistic $z^*(q)$, as provided in equation (13), selecting the maximum absolute value from a set of l test statistics. The test statistic can be written as:

$$MV(q_i)=\max_{1\le i\le l}\left|z^*(q_i)\right| \tag{21}$$

The wild bootstrap variance ratio test can be conducted in three stages, as below:

(i) Form a bootstrap sample of *T* observations $a_t^*=\eta_t a_t,(t=1,...T)$ where η_t is a random sequence with zero mean and unit variance; a normal distribution is used here.

(ii) Calculate $MV(q_i)$ using a_t^* from the bootstrap sample generated in stage (i)

(iii) Repeat stages (i) and (ii) *m* times, for example, 1.000 times in this paper, to form a bootstrap distribution of the test statistic $MV(q_i,j)_{j=1}^m$.

The bootstrap distribution $MV(q_i,j)_{j=1}^m$ is used to approximate the sampling distribution of $z^*(q)$ given in equation (13). The p-value of the test is calculated as the proportion of $MV(q_i,j)_{j=1}^m$ greater than the sample value of $z^*(q)$.

In Monte Carlo simulations, Kim demonstrated that wild bootstrapping variance ratio tests are powerful and robust alternatives for testing the random-walk hypothesis.

3.7 Scoring Model

For a classification and to strengthen our results of the test statistics we made use of scoring model framework. In the building process of the scoring model our criteria to be considered is the likelihood of the CDSs following a random-walk by using the findings of the statistical tests discussed previously. We grouped the daily and weekly data by mean and standard deviation into groups of 2, 3, 5, 6, 10, and 15 (by beginning with the highest value). Tables 3 and 4 give an overview of the mean and standard deviation by each CDS premium for daily and weekly observations on the whole sample period.

Table 3. 3-years-daily CDSs hierarchy criterion

	Bank of America	Barclays	BayernLB	BNP	Citigroup	Commerzbank	Credit Mutual	Credit Suisse	Deutsche Bank	Erste Bank
Mean	130,8546936	104,4972341	101,9509725	66,68574194	189,5755951	89,0086553	82,85414602	88,59916585	85,01785195	165,0807336
Std. Dev.	64,86629986	44,02737896	29,69461359	26,66804929	133,348233	35,90607546	16,74891693	43,15266456	30,04504635	79,88832072

	Goldman Sachs	HSBC	HSH	ING	JP Morgan	LBBW	LBHT	Macquarie	Merill Lynch	Morgan Stanley
Mean	148,618876	66,29828239	192,5398728	86,18421978	76,82485471	117,2708306	108,8114504	226,7099471	195,9603947	218,9469781
Std. Dev.	85,41383078	29,45933326	94,70740844	31,50860556	36,43257667	29,94748324	20,50043827	176,545263	103,0839325	171,2676201

	Natixis	Nomura	NordLB	Rabobank	RBS	Santander	Societe General	UBS	Unicredit	WestLB
Mean	175,9085715	153,2917766	104,2941655	68,71455753	140,9852086	122,351839	91,13524029	110,2081566	85,44125753	128,4422633
Std. Dev.	81,27748818	99,25397355	22,71577923	38,10027693	44,61844192	59,48669476	33,92455644	64,7211344	25,92535805	58,09428332

Table 4. 3-years-weekly CDSs hierarchy criterion

	Bank of America	Barclays	BayernLB	BNP	Citigroup	Commerzbank	Credit Mutual	Credit Suisse	Deutsche Bank	Erste Bank
Mean	132,2217719	105,4190835	102,0772871	67,40837711	190,6145455	89,45609371	83,35530977	89,10242552	85,51332242	165,4319069
Std. Dev.	68,14195276	45,08538812	30,42968009	28,25598777	134,2360244	36,97590313	16,87476937	43,59615161	30,56086868	80,59166713

	Goldman Sachs	HSBC	HSH	ING	JP Morgan	LBBW	LBHT	Macquarie	Merill Lynch	Morgan Stanley
Mean	150,0772936	66,39357474	193,3335187	86,82173067	77,42137036	117,8968777	109,0618349	230,2822219	199,0327564	223,2924291
Std. Dev.	87,2426391	29,67613537	95,81573007	32,61386464	36,78412901	30,58386337	20,4508095	189,6569151	106,582215	185,382174

	Natixis	Nomura	NordLB	Rabobank	RBS	Santander	Societe General	UBS	Unicredit	WestLB
Mean	176,830132	154,0756525	105,014608	69,01168366	141,8650048	123,2874973	92,18039675	110,7190797	87,26832258	129,9435249
Std. Dev.	82,05259876	99,82464572	24,0522336	38,53236169	45,79818507	60,9809604	37,05479549	65,04001555	29,63463782	60,11028041

To determine how well each group member m satisfies the criterion, we assigned a scoring paradigm r_{tmi} by alternative i for every statistical test t in terms of how well it satisfies the criterion. The scoring paradigm has the following structure:

7 Scores: 0% significance within the comprehensive survey

6 Scores: up to 100% significance in the first quarter and 0% significance in the other three quarters within the comprehensive survey

5 Scores: up to 50% significance in the first two quarters and 0% significance in the last 2 quarters within the comprehensive survey

4 Scores: up to 33.33% significance in the first three quarters and 0% significance in the last quarter within the comprehensive survey

3 Scores: up to 100 % significance in the first two quarters and 0% significance in the last two quarters within the comprehensive survey

2 Scores: up to 66.66% significance in the first three quarters and 0% significance in the last quarter within the comprehensive survey

1 Score: up to 100% significance in the first three quarters and 0% significance in the last quarter within the comprehensive survey

0 Scores: exceed 0 % significance in the last quarter within the comprehensive survey

In the next step we chose the relative importance of each statistical test by matching weights w_t. We assigned the Box-Pierce Q-Statistics the weight w=1, Variance Ratio Test by Lo and Mac Kinlay the weight w=1, Variance Ratio Test using Ranks and Signs by Wright the weight w=2 and Wild Bootstrapping Variance Ratio Tests by Kim the weight w=2.

In the following step we computed the aggregated score for each group member:

$$S_m = r_{tmi} w_t \tag{22}$$

In the final step we ranked every group by its achieved scores starting by the highest score result.

4. Results

4.1 Results from the Box-Pierce Q-Statistics

We used a chi-square distribution on 5 per cent level with m degrees of freedom to test the validity of the

random-walk null hypothesis of all 30 CDS for daily and weekly observations. We tested for the existence of autocorrelations by logarithmic means of Q-statistics within the limits of m=1 to 10.

For the daily observations only the CDS of Natixis shows no significance at the 5 per cent level, for all values of m. 9 CDS show a pattern of significances at the first lags (Erste Bank, Rabobank), or at the last lags (Credit Mutual, Credit Suisse, LBHT, Nomura) or at the beginning and at the end of the lags (HSBC, JP Morgan, Macquarie). Furthermore 20 CDS are significant at the 5 per cent level, for all values of m. The value of each CDS increases as m is raised for daily and weekly observations. There is a large difference in the autocorrelation values of Q-Statistics which ranges from 0.0165 (Credit Mutual, m=1) to 78.9984 (RBS, m=10).

For the weekly observations 9 CDS (Credit Mutual, Deutsche Bank, Erste Bank, Goldman Sachs, ING, LBBW, Merill Lynch, Natixis, Macquarie) show no significances at the 5 per cent level, for all values of m. This result conforms only to the daily findings of Natixis. 7 CDS (Barclays, BNP, Commerzbank, JP Morgan, Nomura, NordLB, Rabobank) can be identified to be significant at the 5 per cent level for all values of m. As a comparison only Barclays, BNP, Commerzbank and NordLB conform to the daily observations. Parallel to the findings above there are identified patterns within the remaining 14 CDS. These patterns can be found in no significance at the first lags, at the last lags or at the beginning and at the end of the lags.

As an intermediate result of the daily and weekly findings from the Box-Pierce Q-Statistics it can be ascertained that null hypothesis of a random-walk existing for all values of m is highly possible within the time series of the Natixis CDS.

4.2 Results from the Variance Ratio Tests by Lo and MacKinlay

The variance ratio tests by Lo and MacKinlay check for homoscedasticity and heteroscedasticity to test the existence of a random-walk within the CDS data basis. We compared the results of the Variance Ratio Test with the random-walk null hypothesis at a level of 5 %. For this purpose we made use of a two-sided standardized normal distribution. Furthermore test statistics used aggregation values of q = 2, 4, 8, and 16.

For the daily observations with low values only Credit Mutual, Credit Suisse, Macquarie and Natixis exhibit signs of a random-walk within their time series under homoscedasticity and heteroscedasticity at the significance of 5%. Further, 10 CDSs show no significance at the 5% level under heteroscedasticity at all aggregation levels. Bank of America, Barclays, BayernLB and Erste Bank are significant under homoscedasticity and heteroscedasticity at the aggregation level 2 and 4. Unicredit is significant under heteroscedasticity and homoscedasticity at the aggregation levels 2, 4 and 8. LBBW shows no existence of a random-walk under the assumption of homoscedastic at all aggregation levels. NordLB shows fully significance at all aggregate levels for both homoscedasticity and heteroscedasticity, providing no indication of a random-walk. The rest show differences in rejection and compliance to the random-walk hypothesis. There is a predominant diminishment of positive initial values between q=2 to q=16. Negative initial values don't change in a clear pattern from q=2 to q=16. The highest value of homoscedasticity is for Bank of America (5.0926851 at level 2) and the lowest for NordLB (-5.516824 at level 2). The highest value of heteroscedasticity is for Unicredit (3.270464 at level 4) and the lowest for NordLB (-3.371303 at level 2).

For the weekly observations 20 CDSs are not significantly homoscedastic or heteroscedastic at all aggregation levels. Out of these 20 CDSs only the CDSs of Credit Mutual, Credit Suisse and Macquarie confirm the findings of daily observations. Nomura is significantly homoscedastic at all aggregation levels. Within the daily observations only Nomura is significant on the level 8 and 16. Most of the remaining CDSs are significantly homoscedastic and heteroscedastic at the aggregation level of 2 and/or 4. There is a predominant advancement of negative initial values between the levels of 2 and 16. In comparison to the daily observations Nomura shows the highest value of homoscedasticity (3.275605 in level 4). But as in the daily observations NordLB has the lowest value in the weekly observations (-4.298436 in level 2) as well. The highest value of heteroscedesticity is for Nomura (2.765704 in level 4) and the lowest JP Morgan (-3.006155 in level 2).

As an intermediate result of the daily and weekly findings from the variance ratio tests by Lo and MacKinlay it can be pointed out that only Credit Mutual, Credit Suisse, and Macquarie exhibit no evidence of homo- and heteroscedasticity. Therefore, a random-walk is highly probable only for these 3 CDSs. The remaining 27 CDS likely do not follow a random-walk.

4.3 Results from the Variance Ratio Test Using Ranks and Signs by Wright

The variance ratio tests by Wright analyze the existing of a random-walk with ranks ($R1$, $R2$) under homoscedasticity and signs ($S1$) under heteroscedasticity. The results of the tests have to be transferred to value systems conceived by Wright. The range of numbers that belongs to each value system depends on the number of

observations and on the chosen quantile. To determine the existence of a random-walk within the data we compared the results of the Variance Ratio Test with the random-walk null hypothesis at a level of 5%. Further we used aggregation values of q = 2, 4, 8, and 16 for the variance ratio tests.

For the daily observations 11 CDSs do not exhibit signs of a random-walk within their time series for both *R1* and *R2*. Moreover 4 Banks show no significances at all aggregation levels under the 5 % hypothesis in *R1* (Bank of America, Citigroup, Credit Suisse) or *R2* (Rabobank). BayernLB has no significance at the rank *R2*, but shows significance under *R1* at lag 4. Most of the remaining 14 CDS are not significant at the aggregation level 2 and 4 or level 2, 4 and 8. The highest value for the test on homoscedasticity can be seen in Credit Mutual (12.643859 in lag 16/*R1*) and the lowest in NordLB (-3.961521 in lag 2/*R2*). Under heteroscedasticity (*S1*) we find significant results on all lags for 24 CDS. The other 6 CDS are significant at lag 2 and 4 (BNP, Deutsche Bank, Morgan Stanley) or at lag 2, 4 and 8 (Barclays, Commerzbank, Societe General). For daily and weekly observations there is a predominant diminishment of positive initial values between q=2 to q=16. Contrary to positive initial values, negative initial values change from q=2 to q=16 by raising values.

For the weekly observations 13 CDS are insignificant under both *R1* and *R2* for all levels of aggregation. But these findings are in contrast to 0 CDS that are insignificant under both *R1* and *R2* for daily observations. Further 5 CDS are insignificant at *R1* (Morgan Stanley, Rabobank) or *R2* (Erste Bank, LBBW, LBHT). Nomura and Macquarie show significance for all aggregation levels under *R1* and *R2*. The other 10 CDS mostly are insignificant for lag 2. On the test for heteroscedasticity (*S1*) we find fully significant results by the CDS of Credit Mutual, HSBC, HSH, LBBW, LBHT, Macquarie and Nomura. These 7 CDS are also fully significant under daily observations. Further 12 CDS are fully insignificant, but have no accordance on daily observations. The other 11 CDS are very unspecific regarding their significance to the four chosen lags. This means that there are no specific patterns that can be identified.

As an intermediate result we find no evidence of a random-walk at any of the tested levels for both daily and weekly data.

4.4 Results from the Wild Bootstrapping Variance Ratio Tests by Kim

The variance ratio tests by Kim analyze the existing of a random-walk on a 5 percent level of significance. We use aggregation values of q = 2, 4, 8, and 16.

For daily observations 13 CDS show no significant results for lags of 2, 4, 8, and 16. By contrast, the CDS of NordLB shows significant results for all investigated lags. Most of the other 16 CDS are significant for just q=2 or q=2 and q=4. The highest value within the test statistics is for Barclays (0.991082 in q=16) the lowest value belongs to NordLB (0.000006 in q=2). Noticeable is an increasing value of the test statistic for the most CDSs by raising m's for daily and weekly observations.

For weekly observations 21 CDS are not significant for all of the chosen aggregation levels, while 11 CDS are also not significant under the daily observations. For Nomura we find significant results on all levels, which is in contrast to the results for Nomura in the daily observation (significant for lag 16 only). The remaining 8 CDS are mostly significant on all levels except on lag 2.

As an intermediate result of the daily and weekly findings from the Wild Bootstrapping Variance Ratio Tests by Kim it can be ascertained that a random-walk under all investigated levels within the time series is possible for the following 11 CDS: Bayern LB, Credit Mutual, Credit Suisse, Deutsche Bank, HSBC, ING, LBHT, Macquarie, Morgan Stanley, Natixis and Nomura.

4.5 Results Scoring Model

The results of the scoring models for 3-years-daily mean-ranked, 3-years-weekly mean-ranked, 3-years-daily standard-deviation-ranked, 3-years- weekly standard-deviation-ranked are as follows (see Table 5 to 8):

It appears that subgroups (and their consisting entities) with low values for mean or standard deviation has higher scores and a better rank within the scoring model. This can be tested by dividing the number of subgroups in each group by 2 and adding the sums of the first half and the last half of the subgroups separately. An efficient market implies a high probability for the existence of a random-walk, otherwise it would be an inefficient market. Our findings for the daily and weekly data sorted by mean shows that CDSs with the lowest means have the highest total scores. This implies a high probability for the existence of a random-walk and consequently the highest market efficiency, the lowest speculation and the lowest market manipulation. The same results can be found for the daily and weekly data sorted by standard deviation as low volatilities (as the prices of the derivatives) have the highest market efficiency, the lowest speculation and the lowest market manipulation.

In contrast to this result, companies with a low value for mean or standard deviation are often victims of market manipulation and organized speculations (i.e. by Hedge Funds) as they seem to be traded in an inefficient market with a low probability of a random-walk. Taken as a whole our results show that a company's CDS with a low absolute risk (mean) and a low volatility has higher market efficiency and less market manipulation as compared to companies with high values.

A closer look at the results discloses spikes within the subgroups. In the first moment these spikes seem to weaken our results but as we see the results as a whole these spikes get moderated by the value of the other subgroup members i.e. Table 5: G2_6 (ranked 8th by its mean) achieved with the other 4 by its mean worst-ranked subgroups (G2_7 – G2_10) a total value of 262.63 scores in comparison to 218.482 scores for the 5 best-ranked subgroups (G2_1 – G2_5).

Furthermore our results for daily observations consist of higher scores in comparison to weekly observations. The crucial factor for the different high values for daily and weekly observations depends on the much better performances on Box-Pierce Q-Statistics and Variance Ratio Test Using Ranks and Signs by Wright.

If it comes to the point to choose the scoring model that fits best to the assumption presented above, it can be asserted that for 3-years-daily mean-ranked CDSs groups of 6, for 3-years-weekly mean-ranked CDSs groups of 6, for 3-years-daily standard-deviation-ranked CDSs groups of 15 and for 3-years-weekly standard-deviation-ranked CDSs groups of 3 are the best choices. These scoring models represents best the findings of CDSs with the lowest mean and standard deviation have the highest market efficiency and CDSs with the highest mean and standard deviation have the highest market inefficiency.

Table 5. 3-years-daily CDSs mean-ranked

Groups of 2	Sum	Rank
G1_1	43,33	4
G1_2	24,5	11
G1_3	45,166	2
G1_4	12,5	15
G1_5	37,496	7
G1_6	17,666	13
G1_7	29,324	10
G1_8	29,996	9
G1_9	14,994	14
G1_10	38,158	6
G1_11	40,83	5
G1_12	22	12
G1_13	45,994	1
G1_14	44,996	3
G1_15	34,162	8

Groups of 3	Sum	Rank
G2_1	51,33	5
G2_2	61,666	2
G2_3	32,164	10
G2_4	35,498	9
G2_5	37,824	7
G2_6	36,49	8
G2_7	57,988	3
G2_8	43	6
G2_9	68,99	1
G2_10	56,162	4

Groups of 5	Sum	Rank
G3_1	84,996	3
G3_2	77,996	4
G3_3	55,49	6
G3_4	74,648	5
G3_5	87,824	2
G3_6	100,158	1

Groups of 6	Sum S8	Rank S8
G4_1	112,996	2
G4_2	67,662	5
G4_3	74,314	4
G4_4	100,988	3
G4_5	125,152	1

Groups of 10	Sum	Rank
G5_1	162,992	2
G5_2	130,138	3
G5_3	187,982	1

Groups of 15	Sum	Rank
G6_1	218,482	2
G6_2	262,63	1

Table 6. 3-Years-weekly CDSs mean-ranked

Groups of 2	Sum	Rank
G1_1	61,32	10
G1_2	45,656	14
G1_3	70,478	5
G1_4	37,158	15
G1_5	78,976	2
G1_6	71,972	4
G1_7	65,648	7
G1_8	57,318	12
G1_9	55,314	13
G1_10	81,972	1
G1_11	62,31	8
G1_12	69,148	6
G1_13	73,316	3
G1_14	61,974	9
G1_15	60,312	11

Groups of 3	Sum	Rank
G2_1	98,644	5
G2_2	78,81	9
G2_3	77,812	10
G2_4	110,294	2
G2_5	95,972	6
G2_6	82,308	8
G2_7	112,626	1
G2_8	100,804	4
G2_9	103,97	3
G2_10	91,632	7

Groups of 5	Sum	Rank
G3_1	140,63	6
G3_2	152,958	5
G3_3	167,944	2
G3_4	164,28	3
G3_5	173,444	1
G3_6	153,616	4

Groups of 6	Sum	Rank
G4_1	177,454	5
G4_2	188,106	3
G4_3	178,28	4
G4_4	213,43	1
G4_5	195,602	2

Groups of 10	Sum	Rank
G5_1	293,588	3
G5_2	332,224	1
G5_3	327,06	2

Groups of 15	Sum	Rank
G6_1	461,532	2
G6_2	491,34	1

Table 7. 3-years-daily CDSs standard-deviation-ranked

Groups of 2	Sum	Rank
G1_1	43,33	4
G1_2	25,166	12
G1_3	20	13
G1_4	47,664	1
G1_5	18,666	14
G1_6	26,332	10
G1_7	25,832	11
G1_8	33,33	8
G1_9	44,996	2
G1_10	30,996	9
G1_11	43,994	3
G1_12	38,484	6
G1_13	34,162	7
G1_14	5,664	15
G1_15	42,496	5

Groups of 3	Sum	Rank
G2_1	60,496	3
G2_2	28	10
G2_3	56,664	4
G2_4	35,998	9
G2_5	38,167	7
G2_6	65,996	1
G2_7	49,996	5
G2_8	63,478	2
G2_9	37,162	8
G2_10	45,16	6

Groups of 5	Sum	Rank
G3_1	71,996	4
G3_2	82,83	3
G3_3	64,494	5
G3_4	96,992	2
G3_5	102,978	1
G3_6	61,822	6

Groups of 6	Sum	Rank
G4_1	88,496	4
G4_2	92,662	3
G4_3	104,158	2
G4_4	113,474	1
G4_5	82,322	5

Groups of 10	Sum	Rank
G5_1	154,826	3
G5_2	161,486	2
G5_3	164,8	1

Groups of 15	Sum	Rank
G6_1	219,32	2
G6_2	261,792	1

Table 8. 3-years-weekly CDSs standard-deviation-ranked

Groups of 2	Sum	Rank
G1_1	61,32	9
G1_2	70,978	7
G1_3	9,832	15
G1_4	77,478	2
G1_5	71,644	6
G1_6	61,312	10
G1_7	75,308	3
G1_8	59,646	12
G1_9	72,306	4
G1_10	61,308	11
G1_11	71,984	5
G1_12	82,972	1
G1_13	62,148	8
G1_14	57,312	14
G1_15	58,324	13

Groups of 3	Sum	Rank
G2_1	94,974	7
G2_2	47,156	10
G2_3	114,136	2
G2_4	96,298	6
G2_5	103,298	4
G2_6	103,962	3
G2_7	98,632	5
G2_8	117,632	1
G2_9	92,136	8
G2_10	85,648	9

Groups of 5	Sum	Rank
G3_1	132,798	6
G3_2	158,454	4
G3_3	164,61	3
G3_4	165,27	2
G3_5	185,28	1
G3_6	147,46	5

Groups of 6	Sum	Rank
G4_1	142,13	5
G4_2	210,434	2
G4_3	207,26	3
G4_4	216,264	1
G4_5	177,784	4

Groups of 10	Sum	Rank
G5_1	291,252	3
G5_2	329,88	2
G5_3	332,74	1

Groups of 15	Sum	Rank
G6_1	455,862	2
G6_2	498,01	1

5. Conclusion

Investors hedging portfolios with CDSs need information on the question of whether the increase in speculation affects market efficiency or not. To answer this question our research has examined the relation between the absolute CDS premium and market efficiency. We focused on CDSs for international banks. To check market efficiency we tested the random-walk hypothesis by different test statistics. The strongest version of the random-walk hypothesis was tested by homoscedastic variance ratio tests by Lo and MacKinlay and by nonparametric variance ratio test based on ranks by Wright. The weak form gets tested by Q-statistics portmanteau tests by Box and Pierce, heteroscedastic variance ratio tests by Lo and MacKinlay, nonparametric variance ratio tests based on signs by Wright and wild bootstrapping variance ratio tests by Kim.

We find that for daily and weekly data CDSs with the lowest mean and the lowest standard deviation have the highest probabilities for the existence of a random-walk. Consequently these CDSs are affected by the highest market efficiency, the lowest speculation and the lowest market manipulation. This finding is consistent as CDSs with the highest means and the highest standard deviations have the lowest probabilities for the existence of a random-walk. Therefore these CDSs have the highest potential to trade in an inefficient market with the highest potential for speculation and market manipulation. The results of our analysis show that the CDS market of financial institutions is already a target for market manipulation and speculation. Many of these financial institutions are global players and have become “too big to fail”. Their insolvency would affect other financial institutions, the financial system and the global economy. To reduce speculation we support new regulations on the CDS market. These regulations should safeguard against dangerous speculation and market manipulation in order to protect our quality of life.

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