6. THE FRACTAL STRUCTURE OF CDS SPREADS: EVIDENCE FROM THE OECD COUNTRIES

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Abstract

There is a large and growing literature that criticizes the random walk assumption of the Gaussian distribution and the Efficient Market Hypothesis (EMH) as well. In this respect, the Fractal Market Hypothesis (FMH) is an alternative approach to the EMH. On the other hand, Credit Default Swaps (CDSs) are also taken as an indicator of risk. It is a puzzle for the researchers whether CDS spreads are following a random walk process or not. The aim of this study is to investigate the validity of the FMH in CDS spreads for 34 OECD countries between March 2003 and February 2020. The rescaled range analysis is used for each country's data with four different frequencies. The results show that there is a persistency in all CDS spreads. That process, called the Hurst process, indicates that the Fractal Market Hypothesis is valid in the CDS spreads.

Keywords: efficient market hypothesis, fractal market hypothesis, CDS, OECD countries
JEL Classification: D53, D81, G14

1. Introduction

Louis Bachelier (1900) is a pioneering researcher for the speculation theory in economics. He proposed that markets follow a random walk process. Yet, he could not provide enough empirical evidence for that proposal. The capital markets are not explained by Gaussian distribution or random walk theory (Peters, 1994: 39). On the other hand, one of the components of the risk that investors bear against the return of financial assets is the sovereign risk. In order to measure the sovereign risk, besides the grades of credit rating agencies, Credit Default Swaps (CDSs) are also taken into consideration.

CDSs are insurance-like contracts that provide risk transfer between buyer and seller for a specific credit event. They can also be used for speculation and arbitrage opportunities in addition to hedging for the credit risks. As a result of its flexibility, a liquid market for CDSs has emerged (Gunay and Shi, 2016). Also, there is a relationship between financial market liquidity risk and CDSs. CDSs appear to include a risk premium for market-wide liquidity risk

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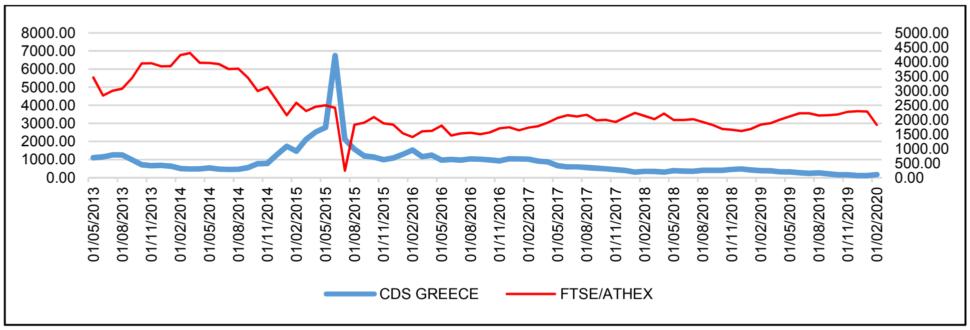
(Van der Merwe, 2015). Various measures of market liquidity risk have been shown to affect CDS spreads, and this statement is extensively studied in the literature (Düllmann and Sosinska, 2007; Fabozzi *et al*., 2007; Gündüz *et al*., 2013; Mayordomo *et al*., 2014; Calice *et al.,* 2015; Meine *et al.,* 2015; Lin *et al.,* 2017). When market conditions get worse and liquidity risk increases, sellers demand a higher CDS coupon rate to recover for the risk (Culp *et al*., 2018). Thus, there is a direct linkage between those, and CDSs could be evaluated as a risk indicator for financial markets. Since CDSs are used as risk indicators, knowing the efficiency of CDS spreads will be beneficial for investors. Therefore, the structure of the CDS market also appears as a structure that needs to be examined. The monthly data for CDS spreads and stock market index (FTSE/ATHEX) of Greece are illustrated in Figure 1. To understand the importance of the CDS market in terms of risk, it should be compared to the stock market index and the CDS rates of Greece, especially during the Eurozone crisis period. While the CDS rates of Greece increased to 6739.21 in June 2015, the stock index dipped to 241.22 in July 2015. It might be said that the market understands the rising level of risk and sellers demand higher CDS rates. The CDS rates gave a signal to investors and the market was crashed. Consequently, examining the structure of the CDS market could be crucial for investors.

Figure 1. The Graphic of CDS Spreads and Stock Market Index of Greece



In the financial literature, the behavior of financial markets has a fundamental assumption that the market data has a Gaussian distribution. This assumption is based on the Efficient Market Hypothesis (EMH). However, there are many studies revealing that the EMH is inadequate. This is one of the much-debated topics in financial literature. Accordingly, the Fractal Market Hypothesis (FMH) is proposed as an alternative to the EMH. The FMH underlines the effect of liquidity and investment horizons on the behavior of markets. The objective of FMH is to generate a model for market behavior and price movements that fits the real world. Thus, one of the counter-arguments against the Gaussian assumption is the FMH. As a result, if the structure of the CDS market needs to be evaluated, whether the CDS spreads show attributes of EMH or FMH is a concept that should be handled to provide practical knowledge for investors.

In this study, analyses are made using the Hurst Exponent (Rescaled Analysis) for CDSs of 34 OECD countries to investigate the existence of the Fractal Market Hypothesis in the CDS spreads. Herein, we focus on whether the CDS markets as a risk indicator have a fractal behavior or not. For this purpose, CDSs of 34 OECD countries are used over the period from March 2003 to February 2020.

The following section summarizes the literature, while section 3 describes the methodology and the data, and section 4 presents and discusses the findings. Lastly, conclusion is presented in section 5.

2. Literature Review

In accordance with the structure of the study, the literature is examined by two groups. In the first group, the studies containing the Fractal Market Hypothesis are examined. In the second group, the studies about CDS of the OECD countries are investigated.

2.1. Studies Containing the Fractal Market Hypothesis

When the studies about FMH from the last decade are examined, one may see that they considered various markets by using a variety of methods.

Kristoufek (2012) investigates whether FMH gives more reasonable predictions than EMH about the dynamics of the financial markets during the turbulences. The result of the study shows that on DJI, NASDAQ, and S&P500, which are the three most liquid US indices, predictions of fractal markets hypothesis actually fit the observed behavior quite well.

Singh *et al.* (2013) state that despite the fact that capital market largely relies upon EMH, other existing hypotheses such as Heterogeneous Market Hypothesis (HMH), Arbitrage Pricing Theory (APT), Capital Asset Pricing Model (CAPM) and Fractal Market Hypothesis (FMH) are equally good. Their study analyzes the prices of State Bank of India (SBI) using Fractal Market Hypothesis and concludes that future prediction of stock prices is possible with the fractal theories developed for the relatively mature market.

Yin *et al.* (2013) examine the gold market of China based on its fluctuation to provide evidence about price movement predictions for investors and managers. They use the R/S analysis and fractal dimension analysis to show that the gold market of China has fractal characteristics. The study shows that the time series of gold returns in China exhibits a nonlinear structure, and the market has statistically self-similar characteristics with long-term memory.

In their study, Kumar and Bandi (2015) test the proposition of FMH, which states that a financial market can experience a crisis when a particular trading time horizon becomes more prominent than others, by using data from two major Indian capital market indices (BSE SENSEX and NSE NIFTY) and one bond market index (NSE GSEC). According to the research, market behavior in the crisis period is said to be compatible with FMH due to the increasing activity among all timescales.

Barna *et al.* (2016) analyzed nine emergent markets by four different estimators of fractal dimension to provide empirical evidence for the potential fractal properties. As a result, emergent markets from Europe and Asia are found to be closer to the ‘non-persistence’ status, while markets from Latin America exhibit more significant signs of local persistence.

Sarpong *et al.* (2016) aim to reveal whether there is chaos on the Johannesburg Stock Exchange (JSE) by analyzing three of its indices with the BDS test described by Brock, Dechert and Scheinkman (1996). The BDS test built upon the FMH shows that all the indices analyzed in this study do not display randomness.

Dar *et al.* (2017) examine whether the claim of the Fractal Market Hypothesis regarding the dominance of certain frequencies during global financial crises is true for the global stock markets. In the study it is shown that higher frequencies predominate during crisis periods on the stock markets around the world, thus confirming the claims of the Fractal Market Hypothesis.

Kumar *et al.* (2017) use a wavelet-based method to test the proposition of FMH that says a financial market could undergo a crisis when a particular trading time horizon gains prominence over the others, for nine Asian forex markets, namely, China, India, Hong Kong, Japan, South Korea, Singapore, Sri Lanka, Taiwan, and Thailand. The study revealed that the 1997–1998 East Asian currency crisis, and the 2008 global financial crisis, were both triggered by increased activity by the short-term traders.

In their study, Wu and Duan (2017) examined gold future price at the Shanghai Futures Exchange (SFE) in China to provide a better understanding of the price fluctuation to investors and help them to make reasonable investment decisions in the gold futures market. The gold futures market, which is found to have the features of memorability, continuation, and periodicity, is found to be a fractal market on the long term. The conclusion that the gold futures market has sustainability in each trading day is drawn, with all Hurst indexes higher than 0.5.

Doorosamy and Sarpong (2018) analyze whether the fractal structure of a financial market is effective in its riskiness and persistence level. As a result, markets with high Hurst exponents are found to have stronger persistence and less risk relative to markets with lower Hurst exponents.

Liu *et al.* (2019) analyzed the efficiency of the Hong Kong Real Estate Investment Trusts (REITs) market in China based on the Hurst exponent. It was found that the Hong Kong REITs market had a lower efficiency than the Hong Kong stock market and the real estate market.

Moradi *et al*. (2021) examine daily, monthly, and yearly time series stock returns on the Tehran Stock Exchange and London Stock Exchange. In the study, the Fractal Market Hypothesis is found to be valid for the Tehran Stock Exchange, whereas it is not valid for the London Stock Exchange.

In a similar analysis to our study, Gunay and Shi (2016) examine the long-memory dependency in volatility of the CDS spreads of Turkey, Russia, South Africa and Brazil. Detrended Fluctuations Analysis (DFA) which is used in the study shows that there is long memory in all markets. Besides long memory parameter magnitudes are calculated by fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model. The study results show that the Efficient Market Hypothesis (EMH) may not hold for the CDS spreads of those four countries.

Çevik and Karaca (2021) investigate the characteristics of Turkey's CDS premiums with ARFIMA-FIGARCH, ARFIMA-FIEGARCH and ARFIMA-FIAPARCH models. They find features close to short memory in the change series and features of long-term memory in the volatility series.

As one may see in the literature, evidences of long-term memory in the CDS premiums are found. Yet, to assess the nature of CDS premiums and to make a more extensive judgment about their fractality, a more comprehensive approach, both presenting the level of fractality and involving more countries, is needed. The innovation that this study brought to the literature is that the fractality of the CDSs of the 34 OECD countries is examined by using the Hurst process and evaluated within fractal classification. As a result, the levels of fractality of the CDSs are presented.

2.2. Studies Including the CDS of the OECD Countries

In this section of the literature review, studies including the CDSs of the OECD countries are examined in relation to their inclusion of CDS.

Broto and Perez-Quiros (2015) state that credit default swap premia of developed countries have become prominent for prefiguring credit risk. By breaking down the CDS spreads of ten OECD countries, they derive a common factor, a second factor impelled by Europe's periphery, and a distinctive component. The aim of this arrangement is to construct a new methodology to characterize contagion among the ten series. They find that contagion’s role in the European peripheral countries after the beginning of the sovereign debt crisis means that there are significant financial linkages between the economies of the countries included in the study.

Min *et al.* (2016) estimate dynamic conditional correlations (DCCs) between equity and currency returns during the financial crisis using Engle's (2002) model for six OECD countries. It is found that the US, Japan, and Switzerland have negative DCCs, they experienced capital inflows, whereas the UK, Australia, and Canada have positive DCCs. In the study, higher country-specific risk, as measured by its country-specific LIBOR interest differential spread, and CDS spread, means higher DCCs. The CDS is found to have a positive and significant association with the DCCs in Australia, Canada, and the UK, and increased CDS results in decreased stock prices and capital outflows from these countries. Yet, the CDS is found to be insignificant for the US, Japan, and Switzerland.

Kim *et al.* (2016) look into the relationships between stock market excess returns, time-varying correlations and volatility of six OECD countries (Australia, France, Germany, Japan, Switzerland, the United Kingdom) and the United States for the US financial crisis and the period after that. Findings of the study suggest that correlation and volatility analysis should include 'excess returns', 'US excess returns' and 'US volatility'. In addition, it is stated in the study that CDS has the power to predict the volatility of France, Germany, and Switzerland.

Bhatt *et al*. (2017) investigate the dynamics of long-term sovereign bond yields for 21 OECD countries. In their research, a dynamic factor model, which divides the variation in bond yields for each country into three factors, which are a common factor, a regional factor and a country-specific factor, is established. The study revealed that, in countries where the regional factor played a more influential role in the period after the 2008 financial crisis, bond yields and credit default swap (CDS) are less sensitive to changes in the debt-GDP ratios.

In their work about the determinants of bank CDS spreads, Benbouzid *et al*. (2017) find that the behavior of bank CDS spreads between OECD and non-OECD countries do not exhibit a significant difference.

Kapusuzoglu and Ceylan (2018) examine the similarities and differences between the OECD countries in terms of the change in CDS risk premiums. The methodology of the study includes Multidimensional Scaling Analysis to calculate the Euclidean distances of the countries. As a result of the calculation, the most similar and different countries in terms of CDS risk premiums are found. According to the results of the study, New Zealand-Australia, Estonia-Austria, Slovakia-Netherlands, Finland-Denmark, and Germany-France are the most similar country pairs, whereas Slovenia-Turkey, Netherlands-Turkey, Russia-Norway, Russia-Mexico, and Slovakia-Turkey are the most dissimilar country pairs. In addition, the countries which are geographically close to each other are found to be very similar in terms of the change in the economic risk level.

3. Methodology and Data

3.1. Methodology

Harold Edwin Hurst (1951) suggested an approach to modeling the fractal structure: Rescaled Range (R/S). Hurst, who was a hydrologist, worked on the Nile River Dam project in the early 20th century. He had studied 847 years of data of the Nile River for the calculation of the storage capacity of a reservoir. The data of the Nile River did not seem a random walk process to him. He realized there were nonperiodic length cycles in overflows. So, he developed his own methodology. The outcome of the analysis is an exponent which is called the Hurst Exponent (H), and it has a range between one and zero (0<H<1). According to the Hurst methodology, if a time series has a Gaussian distribution, then H becomes 0.50. When he analyzed the Nile River data, he found 0.91. That means there is no random walk process in the overflows of the Nile River. Moreover, the changes in the overflows of the Nile River were found to be correlated, meaning that they were affecting each other.

Hurst's method has found its place in economics with the studies of Peters (1991; 1994). The Hurst Exponent can be calculated as follows (Peters, 1994:57; Brooks, 1995:428):

Let say, $\bar{x}$ is the mean of a time series of length n, and S_n is the estimated standard deviation with maximum likelihood:

$$\bar{x} = (x_1 + \cdots + x_n)/n \tag{1}$$

$$S_n = \left(\sum_{r=1}^{n} \sqrt{(x_r - \bar{x})^2}\right)/\sqrt{n} \tag{2}$$

The first rescaled range can be calculated by subtracting the mean, $\bar{x}$, from each observation. Next step is creating the cumulative time series, Y_j.

$$Y_j = \left[(x_1 - \bar{x}) + (x_j - \bar{x})\right] \tag{3}$$

The adjusted range, R_n, is the maximum minus the minimum value of the Y_j. It could be calculated:

$$R_n = \left[\max_{1\le k\le n} \sum_{j=1}^{k}(Y_j - \bar{Y}_n) - \min_{1\le k\le n} \sum_{j=1}^{k}(Y_j - \bar{Y}_n)\right] \tag{4}$$

Hurst, later, found a general form of Eq. 4:

$$R_n/S_n = cn^H \tag{5}$$

where: R_n is the adjusted range; S_n is the estimated standard deviation; c is a constant; H denotes the Hurst exponent; and R_n/S_n is known as the rescaled range. In Eq. 5, there is an estimation problem because it is an exponential model. We need to convert it to a logarithmic model. If we take the logarithm of Eq. 5, we may obtain Eq. 6:

$$\log\left(R/S\right)_n = \log c + H\log n \tag{6}$$

After the estimation of model, a H coefficient of 0.5 indicates random process, as we mentioned above; $0.5 < H < 1$ signifies a persistent time series which shows long memory effects; $0 < H < 0.5$ signifies an anti-persistent process. There is no long memory feature in anti-persistent time series, and the movement in the series tends to return to average (Brooks, 1995:429).

Mulligan (2004:158) created a summary table for the different values of the H exponent in his study. Table 1 shows the noise scale in the series and the distribution of the series according to the different results of Hurst exponent.

Table 1. Fractal Classification of Series

Term	Color	Hurst Exponent
Anti-persistent, mean-reverting, negative serial correlation	Pink noise	0 < H < 0.5
Gaussian process, random walk	White noise	H ≡ 0.5
Brownian motion, Wiener process	Brown noise	H ≡ 0.5
Persistent, trend-reinforcing, Hurst process	Black noise	0.5 < H < 1
Cauchy process, Cauchy distribution	Cauchy noise	H ≡ 1

In Table 1, the Cauchy process states that there is a high probability of sudden and large changes in time series. The time series remaining on the black noise scale have less random motion than other scales. So, they have obvious trends and it is possible to face positive returns by following the historical data. Brown noise is the cumulative sum of a normally distributed white-noise process. The changes in time series are called white noise. The brown and white noise have the same Hurst exponent because the brown-noise process should be differenced as part of the estimation process, yielding white noise. Thus, they state the random walk which the process of data generating is purely random. A time series with a pink noise scale has a more fluctuating appearance than the random walk process (Mandelbrot, 1963a; 1963b; Mandelbrot *et al*., 1997:5; Mulligan, 2004; Aygören, 2008). It is clear that the Gaussian process is rejected if there is Cauchy, Black or Pink noise.

3.2. Data

In accordance with the aim of the paper, the descriptive statistics of CDS returns for 34 OECD countries is presented in Table 2. According to the design of analysis, daily, weekly, monthly, and quarterly frequencies are placed in Panel A, B, C, D, respectively.

Table 2. Descriptive Statistics of the CDS Returns for 34 OECD Countries

Panel A	Daily					
	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Belgium	0.0004	0.0000	0.8935	-1.2040	0.0948	4010
Austria	0.0002	0.0000	6.3722	-6.3511	0.2322	4010
Canada	-0.0003	0.0000	0.1046	-0.0498	0.0135	399
Denmark	-0.0006	0.0000	0.2862	-0.2068	0.0422	2786
France	0.0003	0.0000	1.2489	-1.2489	0.0879	3783
Germany	-0.0001	0.0000	1.7047	-1.3863	0.1001	3929
Greece	0.0006	0.0000	1.7918	-1.6740	0.0933	4010
Iceland	0.0008	0.0000	0.7198	-0.7673	0.0615	4.010
Ireland	0.0000	0.0000	0.6075	-0.6257	0.0416	3159
Italy	0.0005	0.0000	0.4896	-0.4373	0.0424	4.369
Netherlands	0.0005	0.0000	0.8473	-0.9163	0.0761	3749
Norway	0.0002	0.0000	0.6985	-1.2593	0.0536	3157
Portugal	0.0005	0.0000	1.6740	-1.2528	0.0972	4007
Spain	0.0007	0.0000	2.0149	-2.5903	0.1358	4007
Sweden	0.0003	0.0000	1.1239	-0.6931	0.0642	3905
Switzerland	-0.0009	0.0000	0.7909	-0.4260	0.0443	2.886
Turkey	-0.0001	-0.0011	0.2282	-0.2364	0.0314	4.990
United Kingdom	0.0007	0.0000	0.9361	-0.6278	0.0481	3616
USA	0.0002	0.0000	0.6986	-0.6199	0.0531	3179

Panel A	Daily					
	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Australia	-0.0001	0.0000	0.4917	-0.3604	0.0334	2996
Chile	-0.0003	0.0000	0.5407	-0.5501	0.0371	4450
Czech Republic	-0.0006	0.0000	0.4268	-0.3716	0.0334	2823
Estonia	0.0006	0.0000	0.6269	-0.6337	0.0415	3658
Hungary	0.0003	0.0000	0.6931	-0.4568	0.0424	4006
Israel	0.0000	0.0000	0.5094	-0.6242	0.0365	4007
Japan	0.0000	0.0000	0.5978	-0.5985	0.0445	4464
South Korea	-0.0002	0.0000	0.3421	-0.4068	0.0365	4651
Latvia	0.0006	0.0000	0.8882	-0.5911	0.0464	3664
Lithuania	-0.0006	0.0000	0.1795	-0.2366	0.0246	2713
Mexico	-0.0003	-0.0011	0.4545	-0.4160	0.0345	4718
New Zealand	-0.0007	0.0000	0.3575	-0.3196	0.0416	2887
Poland	0.0002	0.0000	0.5970	-0.6242	0.0501	4010
Slovakia	0.0003	0.0000	1.1787	-1.1787	0.0659	4011
Slovenia	0.0004	0.0000	0.9924	-0.9393	0.0524	3982

Panel B	Weekly					
	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Belgium	0.0019	0.0000	0.6931	-1.0116	0.1382	803
Austria	0.0010	0.0000	3.3274	-3.9560	0.2345	803
Canada	-0.0016	0.0000	0.0859	-0.0870	0.0293	80
Denmark	-0.0030	0.0000	0.3914	-0.2596	0.0777	558
France	0.0025	-0.0005	0.9613	-0.9613	0.1192	757
Germany	-0.0004	0.0000	1.7387	-1.3863	0.1819	786
Greece	0.0031	0.0000	1.4626	-1.3062	0.1577	803
Iceland	0.0041	0.0000	1.2528	-0.6664	0.1243	803
Ireland	0.0000	-0.0021	0.8081	-0.3213	0.0881	632
Italy	0.0024	0.0000	0.4797	-0.4915	0.0912	882
Netherlands	0.0015	0.0000	0.8303	-0.6286	0.1220	751
Norway	0.0011	0.0000	0.7940	-1.2290	0.1077	632
Portugal	0.0026	0.0000	1.3545	-1.3218	0.1470	803
Spain	0.0033	0.0000	2.1972	-2.0149	0.2114	803
Sweden	0.0015	0.0000	1.0186	-0.6931	0.1159	782
Switzerland	-0.0046	0.0000	0.6461	-0.4166	0.0872	578
Turkey	-0.0005	-0.0084	0.4925	-0.5829	0.0801	1010
United Kingdom	0.0031	0.0000	0.8109	-0.3777	0.0918	724
USA	0.0013	-0.0002	0.6199	-0.3417	0.0922	636
Australia	-0.0004	0.0000	0.4745	-0.3460	0.0813	599
Chile	-0.0014	-0.0056	0.5724	-0.3958	0.0802	890
Czech Republic	-0.0027	0.0000	0.4232	-0.4028	0.0700	564
Estonia	0.0029	0.0000	0.8107	-0.3751	0.0862	731
Hungary	0.0013	-0.0020	0.7621	-0.6548	0.0942	801
Israel	0.0000	0.0000	0.4810	-0.6242	0.0745	801
Japan	0.0000	0.0000	0.6225	-0.5985	0.0812	892
South Korea	-0.0011	-0.0010	0.5732	-0.5795	0.0904	937

Panel B	Weekly					
	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Latvia	0.0031	0.0000	0.9673	-0.6214	0.0930	732
Lithuania	-0.0032	-0.0024	0.2579	-0.2117	0.0529	542
Mexico	-0.0016	-0.0038	0.8433	-0.6203	0.0885	955
New Zealand	-0.0035	-0.0006	0.4155	-0.3693	0.0878	577
Poland	0.0013	0.0000	0.7143	-0.3862	0.0948	801
Slovakia	0.0013	0.0000	1.1787	-1.1787	0.1327	802
Slovenia	0.0023	0.0000	0.6702	-0.7538	0.0952	796

Panel C	Monthly					
	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Belgium	0.0065	-0.0098	0.8873	-1.0986	0.2279	184
Austria	0.0054	-0.0173	1.4954	-0.6931	0.2408	184
Canada	-0.0071	-0.0153	0.0855	-0.0548	0.0405	18
Denmark	-0.0127	-0.0171	0.6735	-0.6377	0.1537	128
France	0.0110	-0.0169	0.9479	-0.5616	0.1972	174
Germany	-0.0017	-0.0028	1.0019	-1.8971	0.2797	181
Greece	0.0136	-0.0022	1.1920	-1.3073	0.3131	184
Iceland	0.0180	-0.0022	1.6891	-1.0594	0.2525	184
Ireland	-0.0023	-0.0132	0.6931	-0.5607	0.1786	145
Italy	0.0097	0.0000	1.0668	-0.5007	0.1848	203
Netherlands	0.0065	0.0000	1.0480	-0.5596	0.2053	173
Norway	0.0047	-0.0112	1.0006	-1.5217	0.2213	145
Portugal	0.0165	0.0044	1.2040	-0.6931	0.2474	184
Spain	0.0021	0.0000	1.5041	-2.0149	0.3276	184
Sweden	0.0067	0.0000	1.3686	-0.8267	0.2205	180
Switzerland	-0.0215	-0.0199	0.5997	-0.5814	0.1661	133
Turkey	-0.0025	-0.0167	0.5528	-0.3927	0.1697	232
United Kingdom	0.0153	0.0000	1.2528	-0.6965	0.1994	166
USA	0.0041	0.0001	0.6286	-0.8561	0.1821	146
Australia	0.0004	0.0000	1.0009	-0.5686	0.1793	138
Chile	-0.0044	-0.0276	0.7178	-0.3677	0.1662	205
Czech Republic	-0.0100	-0.0058	0.4407	-0.3125	0.1058	130
Estonia	0.0133	0.0000	1.0451	-0.5023	0.1834	168
Hungary	0.0052	-0.0055	0.6424	-0.5306	0.1716	184
Israel	-0.0021	-0.0142	0.4635	-0.5113	0.1393	184
Japan	0.0007	0.0000	0.7582	-0.6592	0.1763	205
South Korea	-0.0030	-0.0104	0.7322	-0.4868	0.1844	216
Latvia	0.0136	-0.0038	0.9376	-0.3565	0.1701	169
Lithuania	-0.0136	-0.0194	0.2596	-0.2459	0.0973	125
Mexico	-0.0050	-0.0307	0.7835	-0.4375	0.1639	220
New Zealand	-0.0152	-0.0043	0.3409	-0.5731	0.1569	133
Poland	0.0058	-0.0107	0.8924	-0.7209	0.1821	184
Slovakia	0.0067	-0.0044	1.3218	-1.0986	0.2238	184
Slovenia	0.0094	0.0000	0.8569	-0.7538	0.1797	183

Panel D	Quarterly					
	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Belgium	0.0178	-0.0515	1.1081	-0.6896	0.3856	61
Austria	0.0162	-0.0424	1.9985	-0.8824	0.4343	61
Canada	-0.0122	-0.0224	0.0519	-0.0671	0.0378	6
Denmark	-0.0378	-0.0348	1.1801	-0.7687	0.2728	43
France	0.0381	-0.0577	1.2058	-0.8744	0.3786	58
Germany	-0.0070	-0.0856	1.3169	-1.3863	0.4085	60
Greece	0.0392	-0.0702	1.3919	-1.7220	0.5980	61
Iceland	0.0544	0.0000	1.9395	-0.8575	0.4334	61
Ireland	-0.0079	-0.0703	1.0975	-0.5442	0.3299	48
Italy	0.0289	-0.0272	1.1381	-0.5884	0.3354	68
Netherlands	0.0195	-0.0404	1.6786	-0.7841	0.3916	58
Norway	-0.0174	-0.0438	1.3297	-1.1297	0.3628	48
Portugal	0.0383	-0.0271	0.9654	-0.7140	0.3718	61
Spain	0.0153	-0.0153	0.8865	-1.1787	0.3790	61
Sweden	0.0200	-0.0209	1.9780	-0.6931	0.4331	60
Switzerland	-0.0638	-0.0584	0.7443	-0.7553	0.2714	44
Turkey	-0.0136	-0.0419	0.6981	-0.6471	0.2734	77
United Kingdom	0.0461	-0.0188	1.4929	-0.5489	0.3817	55
USA	0.0122	0.0003	1.1825	-0.6484	0.3359	49
Australia	-0.0004	0.0000	1.6709	-0.7464	0.3583	46
Chile	-0.0123	-0.0733	0.8565	-0.5461	0.2981	68
Czech Republic	-0.0273	-0.0272	0.5770	-0.4235	0.1908	43
Estonia	0.0332	-0.0281	1.2881	-0.6885	0.3628	56
Hungary	0.0189	-0.0515	1.1645	-0.7027	0.3268	61
Israel	0.0013	-0.0242	0.8829	-0.6418	0.2224	61
Japan	0.0013	0.0000	1.1931	-0.6700	0.3367	68
South Korea	-0.0080	-0.0282	0.9163	-0.5920	0.3088	72
Latvia	0.0316	-0.0302	1.8295	-0.4462	0.3849	56
Lithuania	-0.0403	-0.0234	0.4932	-0.4677	0.1881	42
Mexico	-0.0104	-0.0468	0.7068	-0.6077	0.2585	73
New Zealand	-0.0511	-0.0276	0.5021	-0.7577	0.2505	44
Poland	0.0188	-0.0109	1.2108	-0.5968	0.3321	61
Slovakia	0.0235	-0.0333	1.3218	-1.4469	0.4445	61
Slovenia	0.0335	0.0000	0.9546	-0.7538	0.3141	61

In Table 2, the CDS data include the period between March 2003 and February 2020. One may see that every CDS series have different observations in every frequency. This is a result of the nature of CDS data which is an insurance premium. The data start to generate when a country issues an asset. As a result of that, the beginning points of all CDS premiums are different. While the highest mean values belong to Iceland in all frequencies, the lowest mean values belong to Switzerland. For the standard deviations, although Greece has the highest value, which is 0.5980 in quarterly data, Austria has the highest values in daily and weekly frequencies and Spain has the highest value for the monthly data. However, Canada has the lowest value in all frequencies.

4. Findings

Using daily, weekly, monthly and quarterly return data of the CDS returns of 34 OECD countries, the Hurst Exponent (H exponent) developed by Hurst (1951) is calculated using the R/S analysis (see Eq. 6). In this analysis, which is used to measure whether the observations of one period are independent or dependent of the previous observations, normal distribution assumption is not mandatory. Therefore, whether the data are distributed normally or not is not tested. In the analysis process, CDS returns of each country are included in the analysis with different frequencies. In analyses, four different H coefficients are estimated for each country's CDS returns. Estimation results of the H exponents are given in Table 3.

Table 3. The Hurst Exponents of Country CDS Returns in Different Frequencies

Country	The Hurst Exponents			
	Daily	Weekly	Monthly	Quarterly
Belgium	0.6137	0.6586	0.7132	0.7722
Austria	0.5996	0.6375	0.6731	0.7342
Canada	0.6638	0.6860	-	-
Denmark	0.5700	0.6222	0.6541	0.7444
France	0.6376	0.6710	0.7085	0.6842
Germany	0.6083	0.6406	0.6497	0.7110
Greece	0.6421	0.6587	0.6878	0.7234
Iceland	0.6065	0.6201	0.6563	0.7276
Ireland	0.6372	0.6693	0.6975	0.7673
Italy	0.6314	0.6561	0.6816	0.7219
Netherlands	0.5899	0.6358	0.6503	0.7897
Norway	0.5619	0.6030	0.7111	0.7843
Portugal	0.6532	0.6611	0.6748	0.7659
Spain	0.6398	0.6263	0.6681	0.7568
Sweden	0.5721	0.6167	0.6826	0.7138
Switzerland	0.5979	0.6433	0.6210	0.6863
Turkey	0.6810	0.6713	0.6740	0.7389
United Kingdom	0.6315	0.6713	0.6605	0.7070
USA	0.5829	0.6205	0.6633	0.6456
Australia	0.6527	0.6736	0.6579	0.6650
Chile	0.6356	0.6557	0.6653	0.7017
Czech Republic	0.6013	0.6141	0.6445	0.6663
Estonia	0.6247	0.6340	0.6301	0.7217
Hungary	0.6498	0.6540	0.6947	0.7904
Israel	0.6117	0.6343	0.6425	0.7074
Japan	0.6197	0.6787	0.6730	0.6833
South Korea	0.6589	0.6731	0.6513	0.7136
Latvia	0.6219	0.6431	0.6917	0.7987
Lithuania	0.6149	0.6468	0.6781	0.7642
Mexico	0.6748	0.6587	0.6375	0.7225
New Zealand	0.6063	0.6380	0.6682	0.7389

Country	The Hurst Exponents			
	Daily	Weekly	Monthly	Quarterly
Poland	0.6237	0.6426	0.6835	0.8076
Slovakia	0.6069	0.6302	0.7078	0.7410
Slovenia	0.6215	0.6390	0.6858	0.7051
Average	0.6219	0.6466	0.6709	0.7304

The lowest average value of the H exponent, calculated at different frequencies, is observed in the daily frequency data, with 0.6219. This is followed by 0.6466 for the weekly data, 0.6709 for the monthly data and 0.7304 for the quarterly data, respectively. As one may see in Table 3, average H exponent increases while the frequency decreases. The increase in the average H exponent might have emerged due to central limit theorem, because as the frequency increases, sample size increases; as a result, distribution gets closer to the Gaussian process. Moreover, nearly all estimated H exponents range between 0.50 and 1.00. This means that there is a persistent and trend-reinforcing structure in the CDS market. Thus, it might be said that CDS spreads are characterized by long memory effects. Constitutively, what happens today impacts the future forever, so, all daily, weekly, monthly, and quarterly changes are correlated with all future changes, respectively. It is possible to estimate the next period by following the historical data. In this manner, as a risk indicator, trends of CDS spreads should be pursued well by investors and policymakers.

In the daily frequency data, Norway has the lowest H exponent, 0.5619; on the other hand, Turkey has the highest one, 0.6810. In the weekly frequency data, while Canada has the highest H exponent, Norway has the lowest one, again. However, in the monthly frequency data, Switzerland has the lowest H exponent and Belgium has the highest one, 0.7132. At last, in the quarterly frequency data, while Poland has the highest H exponent, the USA has the lowest one. In every frequency, the country which has the lowest and highest H exponent is changing. The reason for that is the different risk structures of countries and the various time horizons in frequencies. When the frequency decreases, the time horizon of data rises, and the risk of maturity increases as well. It is clear that the CDS market structure of Norway has a very close behavior to the Gaussian process and random-walk in terms of daily and weekly frequency data. Thus, Norway has an independent and uncorrelated risk process; the present CDS spreads do not affect the future.

To conclude, the findings indicate that Fractal Market Hypothesis is valid for the CDS markets of the OECD countries. These results are consistent with the findings of Gunay and Shi (2016). Furthermore, the implications are crucial for investors, policymakers, and practitioners. If they classify the structure of CDS markets as EMH or Gaussian process, it is quite possible that they will make misleading analyses. The persistent and trend-reinforcing structure of CDS markets should be taken into account and the calculations of market risks should be done in this direction.

5. Conclusion

In the financial markets, investors face a trade-off between risk and return. There are various ways to measure the risk in the literature. However, every indicator has its own constraints because of the components of the risk. It is possible to divide the risk into different ways. In the Capital Asset Pricing Model Theory, there are two kinds of risk: systematic and non-systematic risk. Yet, in the risk premium methodology, there are three types of risk in the market: default, maturity and liquidity. It is not wise to use one risk measure to indicate total risk in the market. So, investors also take into account the sovereign risk as a risk indicator. In order to measure the sovereign risk, Credit Default Swaps (CDSs) are also taken into consideration. CDSs can be used for a component of the risk for a financial asset.

It is well known that financial markets are constructed in the framework of Gaussian distribution and random walk theory. However, researchers have found evidence against those assumptions over a half of century. They state that returns are not normal, random walk, and independent and identically distributed (IID). Thus, variance cannot be a measure of risk. Consequently, Fractal Market Hypothesis (FMH) was proposed as an alternative hypothesis to EMH. Accordingly, the structure of the CDS market is required to be evaluated to provide practical knowledge for investors. Whether the CDS spreads show attributes of EMH or FMH is a concept that should be understood by policymakers, practitioners, or investors.

There are several studies that investigate whether CDS spreads follow a random walk process or not. The common findings of those studies emphasize that the EMH may not hold for the CDS spreads. Evidence of long-term memory in CDS premiums is found in certain studies in the literature. However, in order to make a broader assessment of the fractality of the CDS markets, a method that reveals the level of fractality and covers more countries is needed. The novelty of this study is that it examines the fractality of CDS spreads of more countries using the Hurst process and evaluates the CDS markets within the fractal classification. Hence, the purpose of this study is to investigate the fractal structure of CDS spreads as a risk indicator for 34 OECD countries. The data gathered from Bloomberg Professional Terminal is used for the period from March 2003 to February 2020 for four different frequencies (daily, weekly, monthly, quarterly). To investigate the fractal structure, the rescaled range analysis by Hurst (1951) is examined. The Hurst exponents are estimated and reviewed in terms of methodology.

The primary findings show that as the frequency increases, the average Hurst exponents might have converged to Gaussian distribution. Moreover, the country which has the lowest and highest Hurst exponent changes in each frequency. Finally, the CDS markets of all countries have persistency or trend-reinforcing process in every frequency, except for Norway. They have clear trends and there is a possibility to predict the next CDS spread value by following the historical data. These kinds of processes are called the Hurst process. We may easily say that the Fractal Market Hypothesis is valid for the CDS spreads.

A CDS spread might be used as country risk. Moreover, financial markets contain the country's risks as systematic risks. Perception of heightening country risk with rising CDS spreads might lead to falling stock prices. Thereafter, understanding the behavior of CDS spreads may play a key role in access to funding markets for financial institutions. On the other hand, the policy makers (*e.g.*, central bankers) should take account of the results of this paper, since there is a clear connection between CDS spreads and financial markets. For a sustainable economy, policy makers need to control the sovereign risk. To do this, it is crucial that they comprehend the structure of CDSs.

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