9. LONG-MEMORY IN VOLATILITIES OF CDS SPREADS: EVIDENCES FROM THE EMERGING MARKETS

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Abstract

In this study, we analyze the long-memory dependency in volatility of CDS spreads of four emerging markets (Turkey, Russia, South Africa, and Brazil) from 2001 to 2014. Preliminary evidence from Detrended Fluctuations Analysis (DFA) suggests the existence of long memory in all markets. We then use the fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model to estimate the magnitudes of the long-memory parameter. Following the information of modified ICSS test, the Adaptive FIGARCH (A-FIGARCH) and the Time-Varying FIGARCH (TV-FIGARCH) are also employed to control for the potential effects of structural breaks. The results are generally robust with those obtained from the FIGARCH model. The significant long-memory suggests that the Efficient Market Hypothesis (EMH) may not hold for the CDS spreads of those four countries.

Keywords: long-memory, emerging markets, CDS spreads, efficient market hypothesis
JEL Classification: C14, C22, C58, G14

I. Introduction

Credit default swaps are insurance-like agreements used for the risk transfer in a specific credit event between protection buyers and protection sellers. Unlike insurance contracts, they can be traded through spreads which allows them to be used for speculation and arbitrage opportunities in addition to hedging for the credit risks. It is possible to obtain the same return for the same risk by selling CDS without needing any initial capital rather than being exposed to a country's risk by investing in its bonds. These flexibilities provide a liquid market for both protection buyers and sellers. Additionally, CDS spreads have taken the place of bond spreads as a credit risk indicator due to the mentioned advantages and are now monitored by investors more attentively. Although CDSs were blamed following the mortgage crisis (2008-2010), the notional amount of CDS outstanding is still high according to the latest statistics from

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the Bank of International Settlements (BIS). Accordingly, CDSs are the third ranking derivative in terms of the amounts outstanding of over-the-counter (OTC) derivative contracts such as foreign exchange, interest rate, equity-linked and commodity derivatives. Nevertheless, it is worth noting that CDS market share has still been shrinking since the mortgage crisis. According to the BIS statistics, the notional amount of CDS outstanding fell to $19.5 trillion in July 2014, a decrease of $1.6 trillion from July 2013. As seen in the literature concerning CDSs, these instruments have mostly been studied as risk management tools and credit risk indicators. Distinct from the majority of the current literature, this study analyzes the volatilities of CDS spreads of four emerging markets within the context of long memory and structural breaks by using DFA, FIGARCH, A-FIGARCH and TV-FIGARCH models.

Volatility is one of the important parameters in financial modeling and is used in a wide range of fields from derivative pricing to risk management and measurement. For instance, volatility is the most important input in both the Value at Risk analysis and Black-Scholes Option Pricing Model as it needs to be measured while the other variables are observable in the market. Volatility models based on the modeling conditional heteroskedasticity has evolved significantly since the studies of Engle (1982) and Bollerslev (1986), and today many alternative models have been developed that incorporate different stylized facts. Stylized facts in financial time series make it inevitable they be considered in econometric modeling. In fact, different financial assets are not affected by the same events or information sets. As stated by Cont (2001), price information obtained from different assets and markets present different features. However, empirical studies showed that different financial assets such as oil prices in futures market, spot prices of any stock and also currency rates may demonstrate some similar statistical properties even though they are traded in different markets. These apparently random behaviors can provide some non-trivial statistical properties. Prominent ones among these facts can be stated as the fat tails in return distributions, volatility clustering and long memory. Especially the long memory feature, which was presented by Mandelbrot (1972) in the fractal approximation, caused random walk assumption, which is one of the most important assumptions of finance theory, and the Efficient Market Hypothesis of Fama (1970) to be criticized. The assumptions that financial asset returns follow the Markov processes and have no memory are accepted by many financial theories and econometric models. All of these models, from Black-Scholes Option Pricing Model to Capital Asset Pricing Model and GARCH, do not account for memory or short memory conditions.

As stated by Cont (2005) the dependence of financial asset returns, the fat tails in return distributions and volatility clustering have attracted the attention of many researcher and these issues have been extensively studied with the obtainability of high frequency financial data. As a parametric approximation, "long memory" of a shock in volatility and its long-term impact on future volatility were first examined by Engle and Bollerslev's (1986) IGARCH model. The IGARCH model carries most properties of unit root maintaining for the mean. However, shocks are effective on future variance for a finite time horizon and unconditional variance is not present in this model (Poon, 2005). As the IGARCH model is related to the finite resistance in volatility, Baillie et al. (1996) introduced FIGARCH as an alternative model that does not limit differencing parameter as 0 or 1 and enables taking non-integer values between 0 and 1. Mandelbrot *et al.*

(1997) regarded the FIGARCH model as the most important development of that date in the GARCH family. As stated by Baillie and Morana (2009), GARCH, IGARCH and FIGARCH models are members of the same ARCH model family. FIGARCH allows more memory properties in the modeling since it lets differencing parameter take non-integer values different from unity. FIGARCH also can be considered as a generalization of IGARCH model. Baillie *et al*. (1996) displayed the performance of FIGARCH model and stated that long memory feature can be the result of markets aggregation of several different autocorrelated “news” arrival processes. However, today we know that the existence of long memory can arise from structural breaks in returns and these breaks may produce spurious long memory features.

As the countries we analyzed in the empirical section are emerging markets, considering high political risk factors and market conditions, we decided to use long memory models integrated with structural break conditions. Jorion and Zang (2007) showed that Chapter 11 bankruptcies produce dominant contagion effects. Additionally, they demonstrated that an unexpected credit event is the strongest evidence of credit contagion across the industry. Realized defaults in an economy can cause jumps in CDS spreads. Considering this fact and the turbulences which occurred during the period of mortgage crisis we performed modified ICSS test of Sansó *et al*. (2004) and used long memory tests in the presence of structural breaks. There is extensive literature suggesting that structural breaks can produce spurious long memory properties (Hamilton and Susmel, 1994; Mikosch and Starica, 1998; Diebold and Inoue, 2001; Granger and Hyung, 2004). New generation models have been introduced in order to model long memory and structural breaks at the same time. Although in some papers this issue was handled using a manual adjusting procedure regarding breaks (see Choi *et al*., 2010), some integrated models (Smith 2005, Baillie and Morana 2009, Belkhouja and Boutahary 2011) were used in the modeling of variance under long memory and structural breaks. Baillie and Morana (2009) proposed A-FIGARCH model in order to simultaneously account for both long memory and structural breaks in conditional variance. Using simulation models they demonstrated that, in the presence of structural breaks, A-FIGARCH models outperform standard FIGARCH model. Similarly, Belkhouja and Boutahary (2011) introduced TV-FIGARCH for modeling conditional variance considering long memory and structural breaks. In the TV-FIGARCH model, structural breaks were modeled by a logistic function that allows intercept change in time.

Most of the studies concerning long memory in literature focused in stock, currency rate and interest rates and examined the dependency in these markets. In this study we investigated long memory features of volatility of CDS spreads, which is a new generation financial instrument. As to data, we determined four countries from the emerging markets: Turkey, Brazil, South Africa and Russia, since they displayed an economically and politically stable profile in the last decade.

The rest of the study was organized as follows: the second section consists of the theoretical information of the models we used in the empirical analysis. Third section aims to investigate long memory empirically for the CDS spreads of the four countries. The final section presents the results of empirical analysis.

II. Methodology

As described in Diebold and Inoue (2001), long memory is defined using the rate of growth variances of partial sums as $Var(S_T) = O(T^{2d+1})$, where $S_t = \sum_{t=1}^{T} y_t$, $\{y_t\}$ is a sequence of interested financial series and *T* is the number of observations. Then *d* is the long-memory parameter. Empirically, long-memory persistence describes the property of financial series whose sample autocorrelations are significantly different from zero, even for large lags (Ho *et al*., 2013). Different from the short memory, long memory employs a fractional differencing operator model the autoregressive structure of the interested financial series. Hence, those serial correlations will follow a hyperbolic rather than exponential decay. In many recent studies, long-memory persistence is extensively observed, especially for the high-frequency financial series (see, for example, Fleming and Kirby, 2011, and Ho *et al*., 2013).

II.1. Detrended Fluctuations Analysis (DFA)

Since the R/S analysis introduced by Mandelbrot (1972) to test long memory property of financial time series there have many improvements in the form of alternative models. DFA became prominent among these models since it can also be applied to non-stationary time series. As a matter of fact, performance of the DFA has been presented in studies such as Weron (2002) and Günay (2014). Following the definition of Kantelhardt (2009), the calculation of DFA can be summarized as follows: A global profile is obtained for a zero mean time series $\tilde{x}_i$, $i = 1, \dots, N$

$$Y(j) = \sum_{i=1}^{j} \tilde{x}_i, \quad j = 0,1,2,\dots,N, \tag{1}$$

This profile is divided into $Ns = int(N/s)$ non-overlapping sub-segments v of size s. To conduct the detrending procedure, using least squares method, a polynomial trend $y_{v,s}^{m}(j)$ is estimated for every sub-segment v and these trends are subtracted from the original profile $\tilde{Y}_s(j) = Y(j) - y_{v,s}^{m}(j)$. The variance of the detrended $\tilde{Y}_s(j)$ profile of every sub-segment v gives the mean-square fluctuations:

$$F_{DFAm}^2(v,s) = \frac{1}{s}\sum_{j=1}^{s} \tilde{Y}_s^2\,(j) \tag{2}$$

Next, to obtain mean fluctuations $F_2(s)$, $F_{DFAm}^2(v,s)$ are averaged over all sub-segments. Calculating $F_2(s)$ for different values of s, fluctuations scaling exponent H is determined. If the $F_2(s)$ increase with the higher values of s ($F_2(s) \sim s^H$) scaling exponent H ($0.5 < H < 1$) is related to correlation exponent γ: $\gamma = 2 - 2H$.

The intervals of H can be explained as follows: $0.5 < H < 1$ indicates long memory property while $H > 1$ shows non-stationary local average of the data. Finally, if $H < 0.5$, the process has long term anti-correlation, that is, large values are followed by small ones whereas small values are followed by large ones.

II.2. The Modified ICSS Test

Although the normal distribution assumption of financial asset returns have been one of the basic assumptions of many financial theories and models, a significant number of studies have shown that this assumption is fallacious (see Bollerslev, 1987; Susmel and Engle, 1994; and Ho *et. al*., 2013). This truth is also valid for the classical ICSS test of Inclan and Tiao (1994). As demonstrated by Sansó *et al*. (2004) when a studied time series is leptokurtic and conditionally heteroskedastic the classical ICSS test produces spurious results. Hence, the authors utilized κ_2 test as a modified ICSS test. Classical ICSS test can be presented as follows:

$$ICSS = \sup_k |\sqrt{T/2D_k}| \tag{3}$$

where: $D_k = \frac{C_k}{C_T} - \frac{k}{T}$ and $C_k = \sum_{t=1}^{k} \varepsilon_t^2, k = 1, \ldots, T$ is the cumulative sum of squares of ε_t. In conjunction with the refinement of Sansó *et al*. (2004) the new test is free of nuisance parameters for identical and independent zero mean random variables:

$$\kappa_1 = \sup_k |T^{-1/2} B_k| \tag{4}$$

where: $B_k = \frac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}_4}}$, $\hat{\eta}_4 = T^{-1} \sum_{t=1}^{T} \varepsilon_t^4$ and $\hat{\sigma}^2 = T^{-1} C_T$. For the following step the authors introduced the κ_2 test, which takes conditional heteroskedasticity into account, since ICSS and κ_1 are both based on the assumption of independence of the sequence random variables. The authors allow a higher degree of serial dependence by implementing the finiteness of the fourth order moment. Under this property κ_2 test works as follows:

$$\kappa_2 = \sup_k |T^{-1/2} G_k| \tag{5}$$

where: $G_k = \hat{\omega}_4^{-\frac{1}{2}} \left(C_k - \frac{k}{T} C_T \right)$ and $\hat{\omega}_4$ is the consistent estimator of $\hat{\omega}$. Through simulation studies and empirical findings Sansó et al. (2004) demonstrates the robustness of modified ICSS test over classical ICSS.

II.3. The FIGARCH Model

The FIGARCH model proposed by Baillie *et al*. (1996) is extended from the GARCH family models. As concluded by Ho *et al*. (2013), the GARCH family models have enjoyed popularity in finance research because of their ability to capture some of the typical stylized facts of financial return series, such as volatility clustering. French *et al.* (1987) and Franses and van Dijk (1996) show that the GARCH family models take into account the feature of time-varying volatility over a long period and provide good in-sample estimates. The FIGARCH model is particularly designed to model long-memory characteristics of financial series.

Following the definition of Baillie and Morana (2009), if y_t is a discrete time stochastic process with a long memory in its variance and without an autocorrelation in its conditional mean, $y_t \equiv \sigma_t z_t$ is a time-varying measurable function concerning a positive σ_t and the information at $t-1$. For this situation, the FIGARCH (p, d, q) process is as follows:

$$[1 - \beta(L)]\sigma_t^2 = w + [1 - \beta(L) - \Phi(L)(1 - L)^d] y_t^2 \tag{6}$$

where: L denotes lag or backshift operator, and all roots of $0 < d < 1$ and $\Phi(L)$ lie outside the unit circle. The term $(1 - L)^d$ is the fractional differencing operator, and the algorithm to calculate its value is defined in Hosking (1981).

II.4. Adaptive FIGARCH Model

The greatest weakness of the original FIGARCH model is that it fails to account for structural breaks. Therefore, Baillie and Morana (2009) adopt the flexible functional form used in Andersen and Bollerslev (1997) to allow the time-varying components. They propose the Adaptive FIGARCH (A-FIGARCH) model, which is composed of a time-varying intercept by allowing breaks, cycles and changes in drift. More specifically, by allowing the intercept parameter w to become time-varying in conditional variance equation of FIGARCH model, A-FIGARCH model can be exhibited as follows:

$$[1-\beta(L)](\sigma_t^2 - w_t) = [1-\beta(L) - \Phi(L)(1-L)^d]y_t^2, \tag{7}$$

where:

$$w_t = w + \sum_{j=1}^{k}\left[\gamma_j \sin\left(\frac{2\pi jt}{T}\right) + \delta_j \cos\left(\frac{2\pi jt}{T}\right)\right] \tag{8}$$

In particular, if $w_t = w/[1-\beta(1)]$, the above equation reduces to a standard FIGARCH model.

II.5. The TV-FIGARCH Model

The last model we use in the empirical analysis is the TV-FIGARCH model introduced by Belkhouja and Boutahary (2011). The important feature of the model is its ability to consider long memory and structural breaks simultaneously by allowing changes in the baseline volatility dynamics over time. Belkhouja and Boutahary (2011) create the TV-GARCH (p,d,q,R) model to overcome the constant intercept assumption of FIGARCH allowing for time dependency. TV-FIGARCH (p,d,q,R) can be introduced as follows:

$$\left\{\begin{array}{c} \varepsilon_t = z_t\sqrt{h_t}, \qquad \varepsilon_t|\Omega_{t-1} \sim N(0,h_t) \\ h_t = (f_t + \omega_0) + \beta(L)h_t + [1-\beta(L) - [1-\Phi(\mathrm{L})](1-L)^d]\varepsilon_t^2 \end{array}\right\} \tag{9}$$

where: z_t is a sequence of independent standard normal variables with variance 1 and h_t is a positive conditional variance changing by time. f_t can be defined as follows:

$$f_t = \sum_{r=1}^{R} W_r\, F_r(s_t, R_r, C_r) \tag{10}$$

where: $F_r(s_t, R_r, C_r)$, $r = 1, \ldots, R$ is transition functions managing the shift from one regime to another and allowing the intercept of FIGARCH model to fluctuate against time. The main contribution of the TV-FIGARCH model is the addition of f_t to the standard FIGARCH model. When f_t is absent, TV-FIGARCH reduces to standard FIGARCH. The order $R \in \mathbb{N}$ is critical for the determination of the shape of baseline volatility. The switching function for $F_r(s_t, R_r, C_r)$, $r = 1, \ldots, R$ can be exhibited as a logistic transition function as below:

$$F_r(s_t, \gamma_r, c_r) = \frac{1}{1 + \mathrm{e}^{[-\gamma_r(s_t - c_r)]}} \tag{11}$$

where: $s_t = t/T$ is the transition variable with T denoting observation number. γ_r ($\gamma_r > 0$) is the slope parameter and controls the level of smoothness. c_r is the threshold parameter ($c_1 \leq c_2 \leq \cdots \leq c_r$).

III. Empirical Results

In the empirical section, we test long memory property of four emerging markets' CDS spreads namely Turkey, Russia, South Africa and Brazil. All the data used in the study has daily frequency and the sample size consists of 3326 observation during the period between 2001 and 2014. All data was obtained from Bloomberg.

III.1. Data Description

The descriptive statistics of our return variables are summarized in Panel A, Table 1. The mean returns of the four countries are close to 0 (measured in percentage). As suggested by standard error, the unconditional volatility of Russia (3.8733) is slightly greater than the others, while that of Turkey (3.3434) is the smallest. Location statistics like quartiles, minimum and maximum indicate that most CDS returns range from around -30% to 40%. Skewness of the countries are roughly close (at around 0.55), with the exception of Russia which exceeds 0.7. All four rates have large Kurtosis.

To proxy the volatility we use absolute return and the statistics of which are presented in Panel B Table 1. Mean values are roughly similar and range from 2.16 to 2.57. The absolute return of Russia is overall greater than the others, corresponding with the location statistics.

Table 1

Descriptive Statistics

	Mean	SE	Median	Q_1	Q_3	Skewness	Kurtosis
Panel A: Descriptive statistics of returns							
r_t^T	-0.0384	3.3434	-0.1600	-1.6908	1.5425	0.4674	9.2484
r_t^R	-0.0059	3.8733	-0.0925	-1.8565	1.6536	0.7357	14.3881
r_t^{SA}	-0.0021	3.4177	0.0000	-1.4288	1.2463	0.5860	12.0634
r_t^B	-0.0455	3.8050	-0.1330	-1.8628	1.5821	0.5411	17.4115
Panel B: Descriptive statistics of absolute returns							
$\lvert r_t^T \rvert$	2.3061	2.4208	1.6187	0.7153	3.1004	2.8376	16.4902
$\lvert r_t^R \rvert$	2.5691	2.8984	1.7800	0.7228	3.4305	3.5849	27.8302
$\lvert r_t^{SA} \rvert$	2.1637	2.6452	1.3370	0.5060	2.8113	3.1317	18.8993
$\lvert r_t^B \rvert$	2.4966	2.8714	1.7353	0.7152	3.2757	4.0328	34.4721

III.2. Long-memory and Structural Break Test

To examine the existence of long memory, various tests like R/S, V/S, DFA and GPH were derived. Many researchers suggest the DFA test is the most robust as discussed in section 2. Hence, we apply it to absolute returns of the four countries. From Table 2, it can be seen that the null hypothesis of no long memory is rejected in all cases, confirming significant long memory exists for our sample.[3]

[3] We also performed other long-memory tests like R/S, V/S and GPH. The results are consistent and available upon request.

Table 2

Results of the DFA and Modified ICSS Tests

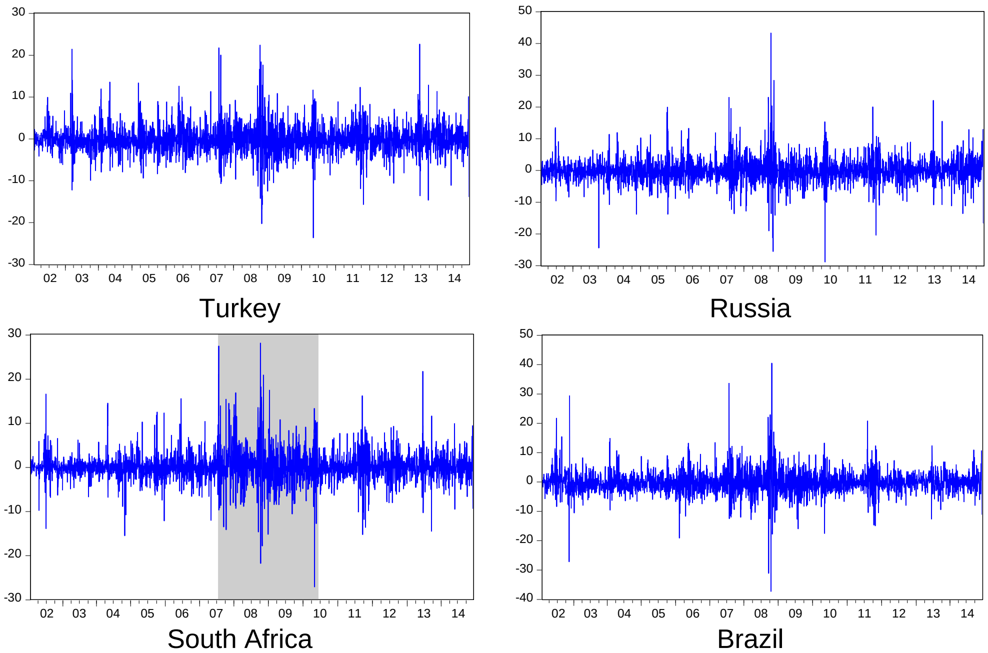
Country	DFA	Modified ICSS: κ_2
Turkey	0.8047^{***}	-
Russia	0.8468^{***}	-
South Africa	0.8240^{***}	07.13.2007 - 06.03.2010
Brazil	0.8474^{***}	-

*, ** and *** indicate the significance at 10%, 5% and 1% level, respectively.

As discussed in Section 1, spurious long memory can be caused by structural breaks so the above results can be misleading if indeed structural breaks do exist in these markets. Figure 1 suggests that all four series are relatively stable over time although they exhibit some volatility during the 2008 global financial crisis (GFC). While the general conditions in the plots of the return series indicate some turbulence, especially during the period of GFC in 2008-2010, we test the existence of structural breaks through the modified ICSS test of Sansó *et al*. (2004) to examine the possibility of that these turbulences produced structural breaks in the returns.

Figure 1

Daily Returns and Detected Structural Breaks



To test the presence of structural breaks at the second moment statistically, ICSS is widely employed among literature. However, as suggested by Inclan and Tiao (1994), ICSS requires that the time series to be i.i.d. and Gaussian. The Kurtosis presented in Table 1 suggested our return series may have fat tails and could be non-Gaussian.

Consequently we perform the modified ICSS proposed by Sansó *et al*. (2004) to test for structural breaks, as it can be used for non-i.i.d. and non-Gaussian series. The results of Table 2 indicate that 3 of the 4 returns have no significant structural breaks, the exception being South Africa. The locations of the detected breaks of South Africa are plotted in Figure 1. The modified ICSS suggests the CDS return volatility of South Africa has a different structure during the 2008 GFC compared to the other periods. All the emerging markets examined in this study were affected by the chaotic environment of GFC in 2008 similar to the European economies. Macroeconomic statistics of these countries gives some explanatory clues concerning the existence of breaks in only the return volatilities of South Africa. For instance, government debt to GDP (GD/GDP) ratio demonstrates that the worst rate of growth occurs in South Africa between 2008 and 2014. In 2008, the GD/GDP ratio in South Africa is 28.3% and in 2014 this statistic raises to 46.1%, climbing 17% in six years. The corresponding rates are %-4.05, %-1.8 and %4.91 in Turkey, Brazil and Russia, respectively (www.tradingeconomics.com). Colombo (2014) finds significant similarities between the processes that occur in USA during the mortgage crisis and in South Africa after the mortgage crisis and predict an economic bubble for South Africa. One of the two lowest interest rate periods in the last decade in South Africa occurs just after the mortgage crisis in 2008 and causes a credit growth exceeding the economic growth rate. More specifically, while the growth rate is 12.7% since 2008, private sector loans increases by nearly 45% during this period. In the same time interval, total outstanding external debt of South Africa rise 87%. The developments which occur in the other countries we examined also reflect to the CDS spreads. The relatively stable economic conditions of other these three economies causes a decoupling process in the CDS spreads. The results of the modified ICSS test corroborate this assertion. Since structural breaks appear not to exist for three of the markets, the detected long memory can truly be present. Hence, we use the FIGARCH model to estimate the magnitude of long memory for our sample.

III.3. The FIGARCH-type Model Results

We fit the FIGARCH (1, d, 1) model for all four series, the results of which are presented in Table 3. Overall, similar to the DFA test, the estimated long-memory parameter d is significantly greater than 0 in all cases. As to their magnitudes, only the estimated d of South Africa is smaller than 0.5 (0.4601). The estimated d of Turkey and Russia are fairly close, at around 0.65, while that of Brazil is smaller and just over 0.5 (0.5278).

Since structural breaks may significantly exist for South Africa, it is useful to control for its effect and see whether long memory is present nonetheless. As described in Section 2, the A-FIGARCH model is a widely used tool to estimate the long-memory parameter while effectively controlling for the influence of structural breaks. Also, when the parameters of γ_j and δ_j are all equal to 0, A-FIGARCH simply reduces to FIGARCH model. Hence, the A-FIGARCH model should generate consistent estimates even if structural breaks are not present.

Table 3

FIGARCH Estimates

	Turkey	Russia	South Africa	Brazil
w	0.4984***	0.9122***	0.7850***	0.7960***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Φ	0.1889***	0.0657	0.0750	0.0029
	(0.0004)	(0.1829)	(0.3258)	(0.9967)
β	0.6623***	0.5378***	0.3466***	0.4275***
	(0.0000)	(0.0000)	(0.0004)	(0.0000)
d	0.6490***	0.6802***	0.4601***	0.5278***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log. lik	-8351.32	-8676.27	-8184.47	-8589.96
AIC	16712.64	17362.54	16378.94	17189.91
BIC	16743.19	17393.09	16409.49	17220.46

Values in parentheses are corresponding p-values. *, ** and *** indicate the significance at 10%, 5% and 1% level, respectively.

We apply the A-FIGARCH (1,d,1,1) model to our sample, and the estimates are presented in Table 4.[4] Compared with results in Table 3, the estimated d of Turkey and Russia are basically unchanged. Also, A-FIGARCH model only increases the log-likelihood to a limited degree in both cases (from -8351.32 to 8350.47 for Turkey and from -8676.27 to -8676 for Russia).

Table 4

A- FIGARCH Estimates

	Turkey	Russia	South Africa	Brazil
w	0.5128***	0.8915***	0.9088***	0.8792***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Φ	0.1815***	0.0709	0.0272	-0.0561
	(0.0016)	(0.1651)	(0.7720)	(0.5223)
β	0.6662***	0.5219***	0.2526**	0.3263***
	(0.0000)	(0.0000)	(0.0315)	(0.0087)
d	0.6583***	0.6552***	0.4077***	0.4717***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_1	0.0588	0.0864	0.4927***	0.6363**
	(0.5192)	(0.5191)	(0.0085)	(0.0123)
δ_1	-0.0881	0.0548	-0.4620**	0.0119
	(0.2789)	(0.7094)	(0.0120)	(0.9483)
Log.lik	-8350.47	-8676.00	-8173.36	-8583.61
AIC	16714.93	17366.00	16360.73	17181.23
BIC	16757.70	17408.77	16403.50	17223.99

*Values in parentheses are corresponding p-values. *, ** and *** indicate the significance at 10%, 5% and 1% level, respectively.*

Consistent with it, estimates of γ_1 and δ_1 are all insignificant. This may be due to the result that structural breaks do not exist for both CDS returns. In terms of South Africa,

[4] Baillie and Morana (2009) suggest that AFIGARCH with a small number of k is adequate and effective. Hence, to keep our model concise, k is set as 1. We also tested k at 2, 3 and 4. The results are consistent and available upon request.

where significant structural breaks are detected, the story is different. The log-likelihood of A-FIGARCH is much greater than that of FIGARCH (-8173.36 compared with -8184.47). Besides, BIC indicates that A-FIGARCH model is preferred to the FIGARCH specification. More importantly, the estimated d is considerably reduced from 0.4601 to 0.4077, which is still significant. In this case, both γ_1 and δ_1 are also individually significant, suggesting that the time-varying constant in the conditional variance equation is appropriate. As for Brazil, although significant structural breaks are not detected, A-FIGARCH also increased the log-likelihood slightly (from -8589.96 to -8583.613), while it is still not preferred by the BIC. The estimated d, it also reduces from 0.5278 to 0.4717 and is still significant.

In conclusion, the FIGARCH model suggests that long memory exists significantly for all the four countries. After controlling for potential structural breaks, results of A-FIGARCH model are consistent, although the magnitudes of estimated long-memory parameters for South Africa and Brazil are smaller than those in the FIGARCH specification. Hence, our empirical results suggest that EMH may not hold for the four countries and these CDS markets are inefficient. According to the definition of Fama (1970), in an efficient market, asset prices fully reflect all of the available information. This definition is based on the assumption that successive price changes (or returns) are independent and identically distributed. These two assumptions consist of random walk hypothesis. Substantially random walk and generally martingale and submartingale models are integrated with Efficient Market Hypothesis and are fundamental assumptions of many financial and econometric models. As stated by Peters (1996), if the EMH is correct, the only factor determining today's price changes is the unexpected news of today. Yesterday's news is no longer important and today's return is uncorrelated with yesterday's return, that is, returns are independent. As a matter of fact, long memory analysis, one of the tools of Mandelbrot's fractal theory, is a robust method to test the weak form of EMH and it has showed great development since the R/S analysis of Mandelbrot (1972). The existence of dependence in returns or volatilities is required to query EMH since it assumes independence and the findings in our analysis support this. While the results of the current long memory studies in finance and econometrics literature provide positive findings in many markets for different assets concerning the invalidity of weak form of EMH, our analysis also present quite robust findings regarding inefficiency of CDS market in emerging markets when taking the existence of structural breaks into account.

III.4. Robustness Check

Apart from the A-FIGARCH model, Belkhouja and Boutahary (2011) propose a TV-FIGARCH model to control for the structural breaks and estimate the long-memory parameter. Hence, we apply the TV-FIGARCH(1,d,1,1) model to test the robustness of our empirical results.[5] The estimates are reported in Table 5.

[5] We also fit other specifications like k=2, 3 or 4. The results are consistent and available upon request.

Table 5

TV-FIGARCH Estimates

	Turkey	Russia	South Africa	Brazil
w	0.4768***	0.8859***	0.7764***	0.7676***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Φ	0.1964***	0.0614	0.0762	0.0108
	(0.0003)	(0.2191)	(0.2163)	(0.8735)
β	0.6666***	0.5301***	0.3407***	0.4340***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
d	0.6437***	0.6832***	0.4521***	0.5258***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
W_1	69.1752	1.7453***	56.2743	94.8677
	(0.8591)	(0.0015)	(0.3267)	(0.4413)
C_1	332.5064	229.0099	795.8403	346.8360
	(0.8313)	(0.3241)	(0.4713)	(0.6373)
R_1	1.0084	0.9309***	1.0000	1.0054
	(0.5231)	(0.0000)	(0.2138)	(0.1982)
Log.lik	-8350.11	-8671.64	-8182.60	-8588.45
AIC	16716.22	17359.29	16381.2	17192.91
BIC	16765.1	17408.17	16430.08	17241.78

*Values in the parenthese are the corresponding p-values. *, ** and *** indicates the significance at 10%, 5% and 1% level, respectively.*

As compared to the FIGARCH model, only the log-likelihood of Russia is greatly increased (from -8676.27 to -8671.64) in the TV-FIGARCH model. Consistent with it, R_1 of Russia is the only individually significant time-varying parameter. In terms of the long-memory parameter, estimated d from the TV-FIGARCH models is very similar to those from FIGARCH models. The largest reduction again occurs for South Africa (from 0.4601 to 0.4521). All the estimated d are still significant, consistent with our results obtained from the FIGARCH and A-FIGARCH models. Finally, as suggested by BIC, TV-FIGARCH model is not preferred in any case, compared with the original FIGARCH model. These results demonstrate the robustness of FIGARCH model against the A-FIGARCH and TV-FIGARCH in the absence of structural breaks.

Following the study of Bachelier (1900), which provide a basis for conventional finance theory, most of the created financial models used random walk hypothesis as a key assumption. Many models such as Capital Asset Pricing Model of Sharpe (1964), Efficient Market Hypothesis of Nobel Prize winner academician Fama (1970), Black-Scholes Option Pricing Model (1973), assume that asset returns follow a geometric Brownian motion and under a Markovian approximation asset prices have zero memory. Since the studies of Benoit Mandelbrot, which criticize the random walk assumption on which asset prices change like the toss of a coin and introduced R/S analysis with Joseph Effect, long memory tests demonstrate that financial asset returns, especially absolute and squared returns, have dependency features. In conjunction with the improvements in modeling, today we can say that long memory is an important stylized fact in financial time series. While there are an abundance of studies for stock markets, we believe that our conclusions regarding CDS markets will be an important contribution to literature. The fact remains that, as stated by Mandelbrot (2004), the dependence or long memory in returns does not imply a foreseeable future. Here, no matter how long memory is denoted, by *H or d,* main concern is the importance of long memory in financial modeling as a stylized fact. We believe that current risk measures or modeling methods, which were built for the existence of zero memory time series, will calculate faulty results; larger or smaller than the actuality. Failure in the measuring of risk will affect the side and magnitude of the position of derivative instruments in hedging causing defective decisions on portfolio selection. Accordingly, using H or d parameters in financial modeling or risk measurement should provide more accurate results.

The problems that started first in the USA mortgage market then spread to the European economies as debt crisis required taking some measures for both sides. Since Turkey and Russia have more interaction with the European economies as compared to Brazil and South Africa in terms of politics and business connection, we can constitute two sub-sets for the countries we analyzed. As one may see from the results, long memory statistics obtained for CDS spreads, which are the functions of default risk and borrowing cost, are larger in Turkey and Russia than the other two countries. High long memory obtained for Turkey and Russia demonstrates the persistence in the volatility of CDS spreads of these countries. Hillerbrand (2003) states that long memory in volatility is also evidence of the uncertainty in relevant data. Hence, higher long memory in volatility also indicates higher risk of the corresponding CDS spread in our study. Since this spread is the cost of the protection against the default risk in underlying asset, as well as any increment in spread is significant per se, volatility properties of the spreads also give some clues regarding the level of risk for the underlying asset. Therefore, higher long memory in the volatility of CDS spreads of Turkey and Russia can be interpreted as persistence in the volatility and as a sign of the uncertainty from the perspective of market participants. While the main objective of this study is not to determine the economic parameters that affect CDS spreads, it is obvious that among the four countries we analyzed, the highest long memory obtained for Turkey and Russia which have relatively higher level of interaction with European economies. As Table 6 shows, between 2002 and 2014 four out of the top five foreign trade partners to which Turkey and Russia export are European countries. In addition to all this discussion, Broto and Perez-Quiros (2015) states that during the period of Euro-area sovereign debt crisis, contagion in the Euro-area has significant effect on peripheral economies' CDS spreads.

As Table 6 shows, while the four of top five economies where Turkey and Russia export are European economies, for Brazil and South Africa this number is only two. On the other hand, the high level of long memory in the volatility of Turkey and Russia's CDS spreads may cause higher required rates of return in investments on these countries due to high level of uncertainty. Rises in required rates of return may cause low offered prices in different fields from bonds to fixed capital investments due to the high discount rates. As this result means low capital inflows, it would not be favorable for emerging markets such as Turkey and Russia.

Table 6

Top 5 Countries in the Export of Turkey, Brazil, Russia and South Africa

Turkey	Brazil	Russia	South Africa
Germany (15.147.400.000)	China (40.616.100.000)	Netherlands (67.969.500.000)	China (8.760.210.000)
Iraq (10.887.800.000)	United States (27.144.900.000)	China (37.496.800.000)	United States (6.467.940.000)
United Kingdom (9.903.170.000)	Argentina (14.282.000.000)	Germany (37.126.800.000)	Japan (4.875.910.000)
Italy (7.141.110.000)	Netherlands (13.035.600.000)	Italy (35.963.100.000)	Germany (4.583.600.000)
France (6.467.860.000)	Germany (6.632.730.000)	Turkey (24.972.300.000)	United Kingdom (3.465.600.000)

Figures within parenthesis are the dollar denominated export statistics for 2014. (Source: Thomson Reuters Eikon)

IV. Conclusion

In this study, we investigate the long-memory dependency in volatility of the four CDS spreads: Turkey, Russia, Brazil and South Africa. Our sample covers a vast range of daily data from 2001 to 2014. The DFA tests suggest the significant existence of long memory in all cases. Results from the FIGARCH model confirm this existence and further indicate that the magnitudes of long memory in volatility are larger in Turkey and Russia compared with those of South Africa and Brazil. As modified ICSS tests demonstrate that potential structural breaks may exist for CDS of South Africa, we also employ the A-FIGARCH and TV-FIGARCH models to control for their effects. The new results are overall consistent with estimates of the FIGARCH model. Therefore, the significant long memory in volatility of CDS spreads suggests that the EMH may not hold for those four CDS spreads.

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