Sovereign Default Swap Market Efficiency and Country Risk in the Euro Area

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Abstract

This paper uses sovereign CDS returns and return volatilities as a proxy for informational efficiency of the sovereign markets and persistency of country risks. We have applied two semi-parametric methods and a parametric dual memory model of long memory to the sovereign CDSs of 11 euro area countries. We test the evidence of long memory behavior for both CDS returns and return volatilities with particular attention to the post credit crunch period. Our analysis reveals that there is no evidence of long memory for the return series of euro area countries, which indicates that price discovery process functions efficiently for sovereign CDS markets. Interestingly, both semi-parametric methods and the parametric model imply persistent behavior in volatility of CDS returns for Greece, Portugal, Ireland, Italy, Spain, and Belgium addressing the fact that highly indebted economies in the euro area face persistent sovereign risk.

Keywords: Credit default swaps, long memory, market efficiency, Eurozone economies

JEL Codes: G01, G14, C58

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1 Introduction

Credit default swaps (CDSs) of sovereign debt have been subject to enormous attention and criticism since the beginning of the credit crunch in mid 2007. Similar to other credit derivatives, sovereign CDSs are financial derivatives that are designed to transfer credit risk between parties. They are mostly used by banks, hedge funds or asset managers to issue complex debt securities in a simpler way by reducing the risk to purchasers. Moreover, CDSs written on sovereign entities have been seen as an important indicator of the economic health of a given country. They shed light on the default risk by signaling how much investors are willing to pay to insure themselves against the country risk.

It is now a clear fact that many euro zone countries suffer from severe public deficit problems that they try to finance through sovereign indebtedness. For instance, Greece, being one of the most indebted countries in Europe, has a public debt level reaching 113% of the country's GDP. Other European countries such as Portugal, Italy, Ireland, Belgium and Spain face similar public debt problems. Given that sovereign CDSs serve as a market indicator of the riskiness of public debt, their return series and volatility patterns are strongly linked to the efficient pricing of public debt and persistence of country risk patterns, respectively (Longstaff et al. (2011), Grossman and Huyck (1988)). An Article in the New York Times on April 29, 2011 reports that "*CDSs played a pivotal role in the global financial meltdown in late 2008. More recently, swaps have emerged as one of the most powerful and mysterious forces in the crisis shaking Greece and other members of the euro zone*".

This paper investigates the long memory properties of sovereign CDSs for 11 euro area countries. CDS returns and CDS return volatilities have been used as a proxy for informational efficiency of the sovereign markets and persistency of country risk. All other things being equal, long-memory behavior of sovereign CDS returns would imply strong predictability and untrustworthy price discovery process where most up-to-date information about the market perception of the sovereign CDSs is not priced correctly. This indeed would create arbitrage possibilities for the issuers of these products. On the other hand, being a proxy for investment risk, the long memory of volatility patterns sheds light on the overall health of the economy and can be used to predict future economic variables such as GDP.[1]

Our analysis follows a two-step process. In the first step we test for long memory behavior for both returns and squared returns employing different tests and robustness parameters. Specifically, we employ log periodogram regression of Geweke and Porter-Hudak (1983) and modified log periodogram regression of (Phillips (2007)) for different ordinate lengths. In the second stage of our analysis we model the long memory of return and volatility of return series using a dual long memory model. The dual memory method, which is a combination Granger and Joyeux (1980) ARFIMA and Baillie et al. (1996) FIGARCH models, allows us to estimate long memory parameters of return series while simultaneously estimating its volatility.

Overall, our results can be decomposed into two. First, we have shown that there is no evidence of long memory behavior for return series for any of the countries in our sample. This indicates that, despite the financial crisis and uncertainty of financial markets, the price discovery processes function efficiently for sovereign CDS markets. On the other hand there is strong evidence of long memory for volatility patterns of return series for 7 out of 11 countries. The countries with long memory behavior in volatility are Greece, Portugal, Ireland, Italy, Spain, and Belgium. This finding indicates that the troubled economies in the euro area which experience serious public indebtedness are exposed to high credit risk not only for a short period but over a persistent horizon.

[1]i.e. Campbell et al. (2001) show that stock market volatility helps to predict GDP growth.

Our paper contributes to several strands of the literature. First of all, this study extends the econometric literature on time series properties of CDS markets. Specifically, we provide evidence of long memory properties for volatility of sovereign CDS returns. Even though CDS prices seem to increase tremendously after the crisis, we have shown that price discovery and information mechanisms seem to function properly. In the light of our results, we can argue that speculative actions using sovereign CDSs through hedge funds or banks are not possible. Previous literature provides evidence of volatility transmissions among CDSs, equity, and bond markets (Belke and Gokus (2011)). If the sovereign CDS market exhibits a long memory behavior in volatilities, this may also trigger the persistency of volatility patterns in local stock markets as well as in the bond markets.

This paper is organized as follows. Section 2 introduces a brief definition of sovereign CDSs as well as effects of long memory behavior to financial time series. This section motivates for the importance of persistency patterns in sovereign CDS return and volatility. Section 3 presents the descriptive statistics of our data set and shows the time series properties of our data. Section 4 provides the results on the semi-parametric testing of long memory for return and squared return series. Section 5 applies parametric dual long memory models to returns and their volatility, while disentangling the short memory components. Section 6 concludes.

2 Motivation

2.1 A Brief Review of Sovereign CDS

CDSs are a class of credit derivatives which is designed to transfer credit exposure of fixed income products or loans, triggered by credit events such as default or failure to pay. In the case of default, the buyer of the CDS is compensated by the notional amount of the CDS. Given that CDS is an efficient diversification instrument under economic uncertainty, the market for CDSs has received special attention in the analysis of credit risk where its spread is regarded as an indicator of potential default risk.[2]

Sovereign CDS contracts are credit derivatives of fixed income government securities. They share many of the features of their corporate counterparts with the exception of the credit event. Typically, credit events of a sovereign CDS contract are (i) obligation acceleration, (ii) failure to pay, (iii) restructuring, or (iv) repudiation/moratorium. Unlike corporate CDS, bankruptcy is not a credit event for sovereign CDS, given that there is no operable international bankruptcy court that applies to sovereign issuers.

Sovereign CDS are traded for a variety of reasons. Among others, Fontana and Scheicher (2010) mention

- Hedging against country risk as an insurance-type offsetting instrument
- Relative-value trading (having a short position in one country and a long one in the other)
- Arbitrage trading (buy/sell government bonds vs sell/buy sovereign CDS)

The first issue has been perhaps the most important motive for the use of sovereign CDS with the start of the crisis in global markets. With increasing sovereign indebtedness of euro zone countries, there exists a serious possibility of contagion (Jorion and Zhang (2007), Longstaff (2010)). After the economic uncertainty in Greece, Ireland and Portugal, now the creditworthiness of larger euro economies such as Spain and Italy are under the spotlight.

2.2 Long Memory Properties of Financial Time Series

Most financial time series indicate unit root behavior at levels, including levels of credit default swaps (Dieckmann and Plank (2011)). Nevertheless, returns of these

[2] For a detailed analysis of CDS contract features, see Gündüz et al. (2007).

series exhibit mostly the properties of martingale differences, which is consistent with the efficient market hypothesis (Tsay (2002), Greatrex (2008)). Although return of a series indicates its performance, volatility of returns (i.e. squared returns) provides information regarding the riskiness of the relevant series. For instance, it is a well-known fact that a relation exists between expected risk premiums of stocks and their volatility (French et al. (1987)).

The long memory of return series has various implications. If returns of a time series display long-term dependence, current realizations are highly dependent on past realizations and remote past can help predict future returns. This distortion in turn gives rise to the possibility of speculative profits, which contradicts the martingale or random walk type behavior that is assumed by many theoretical financial asset pricing models. As mentioned by Lo (1991), optimal consumption/savings and portfolio decisions become sensitive to the investment horizon if stock returns were long-range dependent. Moreover this predictability is inconsistent with the efficient market hypothesis, which assumes prices on traded assets to reflect all past publicly available information (see Mandelbrot (1971), Gil-Alana (2006)).

Not only the return series itself but also its volatility is an important input for investment, option pricing, and financial market regulation (Taylor (2000), Poon and Granger (2003)). Moreover, volatility is used for the measurement of value-at-risk (VaR) in risk management (Jorion (2000)). Implementing VaR is recommended by several international institutions including the Bank For International Settlements, the Federal Reserve and the Securities and Exchange Commission for derivatives market participants. If there is evidence of persistence of volatility patterns for a given series, risk analysis methods that require variance series provide more efficient estimates, when variance of the financial time series is filtered by the long memory model rather than short memory models.

2.3 Why does persistence of sovereign CDS returns and volatility matter?

Although there has been extensive literature on the long memory properties of stock market returns[3] as well as on the long memory properties of stock market volatility, [4] to the best of our knowledge no study has so far concentrated on the long memory properties of sovereign CDSs. Similar to stock market volatility being viewed as an indication of stock market risk, sovereign CDS volatility provides information on country risk and the reliability of underlying fixed income securities. Moreover, Brigo and Chourdakis (2009) showed that credit spread volatility matters considerably in valuing counterparty risk. Not only the level of CDS volatility but also its structure matters. Periods of relatively low volatility or periods of relatively high volatility tend to be grouped together, whereas periods of high volatility tend to occur during recessions (Belke and Gokus (2011)).

Recent empirical literature documents the relation of risk and volatility (Krainer (2002)) and finds a significant relation of economic variables and CDS volatility. For instance, high sovereign CDS volatility is positively related to volatility of economic variables such as inflation and debt level. Given the importance of volatility patterns of CDS, the persistency of volatility becomes vital as well.[5] The speed of forgetting large volatility shocks in financial markets is important for at least two reasons. First, persistent high volatility may imply persistent country risk. Second, a persistent volatility can be used to predict the structure of stability of future economic variables.

[3] See Greene and Fielitz (1977), Jacobsen (1996).

[4] See Crato and de Lima (1994) and Bollerslev and Mikkelsen (1996).

[5] If values from distant time points have a significant impact on more recent time points, the series are said to be persistent (fractionally integrated) and have long memory.

3 The Data Set

In this section we present the descriptive statistics and time series properties of our data set. The first subsection presents the basic descriptives and addresses the sample of interest, as well as the reasons for sample selection. The second subsection investigates the time series properties of the sample period.

3.1 Descriptive Statistics

Time series data of CDS prices are collected from the Markit database, which provides financial information services. We use observations of 10-year senior sovereign CDSs for eleven European Union countries.[6] All quotes are based on euro-denominated CDS contracts which are extensively traded in the market. Countries covered for the analysis are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain, which are members of the European Monetary Union and share the euro as their common currency.

Figure 1 presents the levels of sovereign CDS spreads from January 2004 to October 2011.[7] Figure 1 clearly indicates that in almost all countries, prior to August 2007 the CDS spreads are mostly stable. However with the start of credit crunch, all of the series start to fluctuate considerably and the spreads for all countries increase very sharply. The visual examination of Figure 1 shows a clear difference of the series for pre and post August 2007 periods which most probably address a structural change. In an article on BBC News on 9 August 2009 with the title *"Timeline: Credit crunch to downturn"* it is mentioned that *Defined as "a severe shortage of money or credit", the start of the phenomenon (Credit crunch) has been pinpointed as August 9, 2007, when bad news from French bank BNP Paribas triggered a sharp rise in the cost of credit,*

[6]According to Dieckmann and Plank (2011), 10-year contracts are more liquid than 5-year contracts. Our results remain robust when 5-year contracts are used.

[7]We have interpolated one data point for Greece and 47 for Ireland for the earlier periods where sovereign CDS data were not liquid.

and made the financial world realize how serious the situation was. We have therefore defined the start of the crisis as August 9, 2007.

We first utilize daily observations which span the period from January 2004 to October 2011. Prior to 2004, sovereign CDS market for advanced economies were neither traded liquidly (Dieckmann and Plank (2011)) nor available for many countries. Table 1 and Table 2 show the summary statistics for CDS spread levels in basis points before and after August 9, 2007. Given the pronounced differences between the two periods, we present the descriptives separately.

Table 1 and Table 2 present substantial differences among 11 countries both before and after the credit crunch. Concentrating on Table 1, it is seen that average spreads are as low as 2.7 and 2.9 basis points for Finland and the Netherlands, while as high as only 17 and 19 for Italy and Greece respectively. Even before the credit crunch, spreads in Greece, Italy and Portugal are much higher compared to the rest of the euro countries. Low standard deviations among sampled countries highlight the little variation of spreads before the start of the crisis. Presented also in Table 1 are the skewness and kurtosis statistics of CDS spreads, indicating that the level series tend to have higher peaks and fatter-tail behavior than normal distribution. Finally, Jarque-Bera (J-B) statistics reject normality for all countries at the 1% level, indicating that there are significant departures from normality.

Focusing on Table 2, it is seen that the mean values of CDS levels change tremendously after 9 August 2007. Among the 11 countries, the highest average spread is obtained for Greece with a value of 568 basis points, followed by Ireland with a value of 233 basis points. Following these two, Portugal, Italy and Spain are the countries with relatively higher average spread values. An interesting finding is that before the crisis, spread values for Spain and Ireland are close to the spread values for Germany and France, which are considered to be stable economies. However, during the post crisis period, spread levels for these two joined the group of riskier countries such as Greece and Portugal, indicating that the sovereign debt risk for these two countries increased with the start of the crisis. Not only the mean values but also the maximum values of the spreads shed light on the change in levels. Even for Germany, the maximum value of the spread is 10 times greater after the crisis.

Table 2 also presents the standard deviations of sampled countries for the crisis period. Standard deviations highlight the variability of spreads during the crisis period. For instance, Greece with a deviation of 936 basis points indicates a huge variability, whereas at the other extreme, Germany with a deviation of 21 basis points is much more stable. Not only do the deviations for the crisis period differ among countries but deviations for all countries also exceed the pre-crisis period. For instance, variability in Greece is 170 times more for the post-crisis period. Finally, for the crisis period, skewness and kurtosis values indicate higher peaks and fatter tails whereas J-B statistics again reject normality of the series.

Table 3 and Table 4 present summary statistics for CDS returns.[8] Contrary to the levels in the pre-crisis period, the return series of 11 countries seem to be rather similar. For instance, not only mean returns but also minimum or maximum returns are close for almost all countries.[9] On the other hand, for the post-crisis period there are still substantial differences among the descriptives of the return series. For instance, the mean return in Greece is 2 times more than in Germany or Finland, where minimum and maximum returns are very different, with a range of -0.56% (Greece) to %0.54 (France). Moreover, there are still huge variations of returns when compared with the pre-crisis period. Distributional characteristics of spreads seem to show similarities with the returns before and after the crisis. For all countries, distribution of returns are positively skewed and have very long right tails. Finally, J-B statistics also indicate significant departures from normality for returns.

All in all, the descriptives of the sovereign CDS spreads for both levels and returns

[8]The return series addressed in this paper are log returns calculated as $R_t = log(X_t/X_{t-1})$.

[9]The maximum and minimum values as well as standard deviations for the Netherlands and Finland differ somewhat from the rest of the sample for the pre-crisis period given that the samples for these two countries start in June 2006 and May 2006, respectively.

highlight the transformation before and after August 9, 2007. We believe that this break addresses a structural difference, and analyzing the whole period may cause spurious long memory evidence.[10] Given this reasoning, we restrict our sample to the period after August 9, 2007, and perform our analysis only for the crisis period.

3.2 Time Series Properties

It is important to examine the time series properties of the CDS returns and squared returns before starting with further econometric analysis. To the best of our knowledge, very few studies deal with the time series properties of CDSs.[11] Testing for unit root, Cremers et al. (2008) find no strong evidence of unit root behavior for levels of CDS spreads whereas Dieckmann and Plank (2011) find evidence of non-stationarity for Finland, Greece and the Netherlands.

A generally accepted way of defining long range dependence is in terms of autocorrelation functions. A stochastic process with autocorrelation function $\rho(k)$ is said to have long memory if

$$\sum_{k=-\infty}^{\infty} \rho(k) = \infty. \tag{1}$$

This process has an autocorrelation function which decays so slowly that their sum does not converge to zero.

Given the above reasoning, we concentrate on the autocorrelation functions of returns and squared returns of CDSs. If a series exhibits long memory structure, sample autocorrelations for returns or squared returns should tend to decay slowly and remain fairly large for long lags (Ding and Granger (1996), Bollerslev and Mikkelsen (1996), Ding and Granger (1996)). Looking at Figure 2, it is seen that return series do not

[10]The fact that structural breaks may mimic long memory behavior has been addressed by Granger and Hyung (2004).

[11]Gündüz and Uhrig-Homburg (2011) look at the cross-sectional and time series prediction capabilities of CDSs.

exhibit lag correlations with distant observations.[12] The autocorrelation of the return series disappears after the first lag, which typically has coefficients around 0.15. The rest of the lags are almost always in 95% confidence bands among all countries. The autocorrelation function of return series suggests no evidence of long memory.

Contrary to return series, the autocorrelation function of squared returns decays slowly and exhibits long memory behavior. In almost all countries other than Ireland, distant lags are out of 95% confidence bands. Especially in Netherlands, Belgium and Greece, the autocorrelation bars are out of confidence bands until the 10th lag and the autocorrelation function of squared return series suggests evidence of long memory.

Before starting with long memory tests, it is necessary to examine the unit root behavior and stationarity of the series of interest. In order to test for unit root as well as stationarity, we apply in total three different tests to both returns and squared returns. We utilize modified the Dickey-Fuller(DF-GLS) (Elliott and Stock (1996)) unit root test, the Phillips-Perron(P-P) (Phillips and Perron (1988)) unit root test and the KPSS (Kwiatkowski et al. (1992)) stationarity test. The null hypothesis of the KPSS test differs from the DF-GLS and P-P tests. The DF-GLS and P-P tests tests have the null hypothesis that time series exhibit unit root behavior whereas the KPSS test has the null of trend stationarity. The distribution of the KPSS test under the null hypothesis assumes short memory, implying rejection of both unit root and stationarity tests. This may signal the presence of long memory of the series in these countries (Lee and Schmidt (1996), Su (2003)).

Table 5 shows the results of these three tests for both returns and squared returns. For the return series of 11 countries the DF-GLS and P-P tests reject the null of unit root, indicating return series do not follow unit root process and can be modeled or tested with standard methods. Similarly, squared return series do not exhibit unit

[12]We also graph the autocorrelation functions for the pre-crisis period. Autocorrelation functions for the pre-crisis period demonstrate no evidence of long memory behavior, even for squared return series. The crisis period has longer lag effects for all countries for both returns and squared returns. Figures of the pre-crisis period are not included in the paper but are available upon request

root behavior either. Additionally the first lag of the KPSS test fails to reject the null of stationarity for return series at the conventional level (%1), indicating that return series neither follow unit root behavior nor are non-stationary. On the other hand, for the squared returns, the first lag of the KPSS test rejects the hypothesis of stationarity for Austria, Spain, Netherlands, Finland, Portugal and Germany. As mentioned by by Su (2003), the rejection of both null hypotheses (unit root and stationarity) may simply reflect the existence of long memory for these countries.

4 Preliminary Analysis of Long Memory

In this section we present a preliminary analysis of persistency (long memory) behavior of sovereign CDSs. The first subsection introduces the definition of the statistical tests employed, whereas the second subsection presents the results for the financial crisis sample (after August 9, 2007). The last subsection can be considered as a robustness analysis where the sample is restricted such that it corresponds to the post Lehman collapse period (after September 15, 2008)

4.1 Statistical tests for long memory

Geweke and Porter-Hudak (1983) (GPH) log periodogram regression is the most pervasive approach for testing the fractional integration of a time series. GPH provides a semi-parametric estimator of long memory parameter(d) in the frequency domain in which first the periodogram of the series is estimated and then its logarithm is regressed on a trigonometric function (see Banerjee and Urga (2005) for a detailed discussion).

For a fractionally integrated process X_t of the form

$$(1-L)^d X_t = \epsilon_t \tag{2}$$

the differencing parameter d being the slope parameter of spectral regression in Equation 3, which is

$$ln(I_x(\omega_j)) = a - d \cdot ln|1 - e^{i\omega_j}|^2 + \nu_j \tag{3}$$

where $I_x(\omega_j) = \nu_x(\omega_j) \cdot \nu_x(\omega_j)^*$ is the periodogram of X_t at frequency ω_j. ω_j represents harmonic ordinates $\omega_j = \frac{2\pi j}{T}$,$(j = 1, \ldots, m)$ with $m = T^\lambda$. Discrete Fourier transform (DFT) of the time series X_t is defined as $\nu_x(\omega_j) = \frac{1}{\sqrt{2\pi m}} \sum_{j=1}^{m} X_t e^{i\omega_j}$

The choice of λ parameter is crucial given that a high number of ordinates would induce bias to the estimator, while including too few ordinates would make the OLS regression less reliable. Standard value suggested by Geweke and Porter-Hudak (1983) and Diebold and Inoue (2001) is 0.5, which leads the power function to be $\sqrt{T}$.[13]

For $|d| < \frac{1}{2}$, the DFT and periodogram are non-stationary. Given the economic upheavals in countries (i.e. Greece) for the period of interest, there is no apriori reason to believe that $|d| < \frac{1}{2}$. Modified log periodogram regression (MLR) (Phillips (2007)), whose consistency property for $\frac{1}{2} < d < 1$ is provided by Kim and Phillips (2006), can be employed especially for the series where non-stationarity is suspected.

Phillips modification of the DFT is given by

$$\nu_x(\omega_j) = \frac{\nu_x(\omega_j)}{1 - e^{i\omega_j}} - \frac{e^{i\omega_j}}{1 - e^{i\omega_j}} \cdot \frac{X_t}{\sqrt{2\pi m}} \tag{4}$$

where deterministic trends should be removed from the series before the application of the estimator.

Both the GPH and MLR estimates are based on log-periodogram regressions that utilize the first T^λ frequency ordinates. Besides the typical value of 0.5 for λ we also employ 0.55 and 0.60 in order to evaluate the sensitivity of our results, following Barkoulas et al. (2000).

[13]Other studies such as Cheung and Lai (1993) also employ values around 0.5 for robustness.

4.2 Persistence after the start of crisis

Table 6 shows the long memory tests for both returns and squared returns for the period after August 9, 2007. The first part of the table concentrates on returns, while the second part shows the long memory estimates for squared returns. The first, third and fifth columns of the table present the GPH estimates for power values of 0.50, 0.55 and 0.60, respectively, and the seventh, ninth and eleventh columns correspond to the estimates of the MLR for the same power values.

4.2.1 Long memory of the return series

As seen from the first part of Table 6, the GPH estimates show no significant evidence of persistence of return series for 8 of the 11 countries. Utilization of different powers of the GPH shows that results are robust in terms of including more ordinates (i.e. the inclusion of more ordinates do not change the results). For Ireland, Finland and the Netherlands there is weak evidence of long memory for power value of 0.55 and no evidence even for higher power values.[14] This inconsistency among different power values suggests that for these three countries long memory is rather unreliable and could be the consequence of short-term effects.

Under the MLR for 6 of the 11 countries, conclusions from GPH are confirmed, so that there is no statistically significant evidence of long memory. Furthermore, MLR estimates for Ireland show no significant long memory evidence, either. All in all, Austria, Belgium, Italy, Spain, Portugal, Greece and Ireland exhibit no significant evidence of long memory in returns, implying that return processes do follow efficient market hypothesis and are not predictable.

On the other hand, MLR estimates show statistically significant and consistent evidence of long memory for Finland and the Netherlands. Moreover, the estimated long memory coefficients for these two countries are higher than 0.5, indicating that the es-

[14]Normally, it is expected that the inclusion of more ordinates would increase the possibility of long memory effect.

timates of the MLR are more reliable compared to the GPH. As mentioned above, the evidence of long memory for the Netherlands and Finland could be due to short-term effects. We have shown through autocorrelation graphs that return series in neither of the countries show long memory behavior. Moreover, their return series are almost constant until the second quarter of 2008 for these two countries, which may cause a spurious long memory effect. If the second argument is true, we should see no long memory behavior for the post Lehman period where invariant parts of the sample are not employed. Contrary to the GPH, we observe evidence of long memory for Germany and France. Again for France and Germany, the long memory effect could be the outcome of short memory components (such as AR(1) for France) which are evident from autocorrelation graphs.

4.2.2 Long memory of the squared return series

The second part of Table 6 presents the estimates of long memory for squared returns, which is a proxy for return volatility. Contrary to return series, for which the evidence of long memory is not present for many countries, there is evidence of long memory for squared return series for almost all countries. Moreover, the evidence is mostly robust across different power levels and models.

Although there is evidence of long memory for almost all countries, there is no evidence of long memory for Finland and Austria. Across all power levels and for both GPH and MLR, evidence on persistence of volatility does not exist. There is a weakly statistically significant evidence for France for the highest power value (0.6) for both of the tests, implying that for France squared returns are also less likely to have long memory. Moreover, there is weak evidence of long memory for the lowest power value (0.5) for the Netherlands. Inclusion of more ordinates would increase the possibility of capturing a long memory effect. However, we have a reverse structure for the Netherlands, which implies rather weak evidence of long memory that requires further analysis.

For all power values for Greece and Belgium, evidence is robust for both models. This addresses long memory for squared returns for these two countries. Portugal, Italy and Germany follow Greece and Belgium and present long memory behavior for both models and for all power values other than the power value of 0.5 for the GPH. There is evidence of long memory for Spain and Ireland with the inclusion of more ordinates, which indicates further analysis would be beneficial for these two countries.

Concentrating on the magnitudes of estimated long memory coefficients, it is seen that Greece and Belgium have the highest fractional difference parameters among all specifications. This indicates that persistence of risk exhibits explosive behavior for these countries.

Among the 11 countries, Greece has the highest public debt, followed by Italy and Belgium. All these three countries are experiencing serious difficulties in terms of sovereign debt and credit ratings. Portugal and Spain are considered the eurozone's other indebted countries open to sovereign debt repayment problems after Greece, Italy and Belgium. Finally, Ireland has experienced a debt crisis as a direct result of its housing bubble and accepted a massive international rescue package in 2010.

4.3 Persistence after Default of Lehman

As mentioned by Granger and Hyung (2004), a linear process with structural breaks can mimic properties of long memory processes. As a robustness check to the previous subsection, we employ an alternative break date where the structural change in time series property may happen. Dieckmann and Plank (2011) argue that only after the default of Lehman Brothers did the effects of the market turmoil significantly affect sovereign credit risk. Following this argument we utilize the default of Lehman (September 15, 2008) as an alternative break point.

Table 7 shows the long memory tests for both returns and squared returns for the period after the default of Lehman. The first part of the table concentrates on returns whereas the second part concentrates on squared returns. The first, third and fifth columns of the table present the GPH estimates for power levels of 0.50, 0.55 and 0.60, respectively and the seventh, ninth and eleventh columns are the estimates of the MLR for the same power values.

Confirming the results of the previous subsection where the break point was selected as August 9, 2007, return series exhibit very little evidence of long memory. In addition to the lack of persistency for 7 countries, the evidence in France, Germany and the Netherlands become very weakly significant and inconsistent among different tests and powers. This result confirms that in these for 3 countries evidence of long memory for returns is rather implausible. Evidence still exists only for Finland for higher powers of the MLR test.

Contrary to returns, the evidence of long memory for squared returns becomes even more pronounced among all countries when post-Lehman period is considered. In addition to the more dominant effects through all countries, there is some evidence of long memory even for Austria. Still, Greece and Belgium have the most dominant effects among both specifications and power values. For the Netherlands and France, effects become more significant, whereas for Italy, GPH estimates lose their statistical significance.

The results of this section show that return series of CDS show little evidence of long memory, suggesting that series are efficient. However, contrary to returns, as a result of increased uncertainty and country risk, the volatility patterns of sovereign CDSs in Greece, Belgium, Italy, Spain, Portugal and Ireland are persistent and volatility shocks die out very slowly. The possible reasons for persistence for Germany, France and the Netherlands are analyzed in the next section, and it is shown that evidence of long memory is mostly related to short-term effects, but not to persistency of risk.

5 Dual Persistence and Volatility Clustering

The limitation of the semi-parametric methods such as the GPH or MLR is that they use two-step estimation procedures in which the short memory effects in the series may bias their results. The problem with this type of estimation methodology is using information only at low frequencies. Therefore, the short-term properties of the financial series are not taken into account when estimating the fractional differencing parameter. As a result of this approach, long-term parameters could be contaminated by the presence of short-term components. In this section, we address this issue and re-estimate the long memory evidence using parametric models. Specifically, we employ the dual long memory ARFIMA-FIGARCH model. The first subsection of this section introduces the details of the dual long memory model; the second subsection presents the estimation results.

5.1 Parametric methods of Long Memory: ARFIMA-FIGARCH

We first introduce the parametric methods to estimate the components of dual memory. The returns that correspond to the mean equation are estimated using an ARFIMA model, whereas the conditional variance is estimated using a FIGARCH model.

5.1.1 ARFIMA model

In order to model long memory of the return series, the ARFIMA(p, ξ, q) model, which is developed by Granger and Joyeux (1980), is employed. ARFIMA(p, ξ, q) can be expressed as

$$\begin{aligned} \phi(L)(1-L)^{\xi} X_t &= \theta(L)\varepsilon_t \qquad (5) \\ \varepsilon_t &= \sigma_t * z_t \end{aligned}$$

where L denotes the lag operator, ϕ and θ are polynomials in the lag operator of orders p and q whose roots lie outside the unit circle. The error term ε_t follows a white noise process through $z_t \sim N(0,1)$ with variance σ^2. The key component of Equation 5 is the fractional differencing parameter which is represented as ξ. It identifies the magnitude of long memory (i.e. $\xi = 0$ represents ARMA(p, q))

5.1.2 FIGARCH model

In order to capture the long memory of conditional volatility, FIGARCH(p, d, q) by Baillie et al. (1996) is employed. FIGARCH(p, d, q) can be expressed as:

$$\phi(L)(1-L)^d \varepsilon_t^2 = \omega + [1 - \beta(L)]\upsilon_t \tag{6}$$

where $\upsilon_t = \varepsilon_t^2 - \sigma_t^2$. To ensure stationarity, roots of $\phi(L)$ and $[1 - \beta(L)]$ lie outside the unit circle. As in ARFIMA, the fractional differencing parameter d for FIGARCH is vital which identifies the magnitude of long memory (i.e. $d = 0$ represents GARCH(p, q) or $d = 1$ represents IGARCH(p, q))

5.2 Empirical Results

Table 8 shows the estimates of the dual memory model for 11 euro area countries.[15] μ and ω are the constants for ARFIMA and FIGARCH models, respectively. AR(1) is the autoregressive parameter where MA(1) is the moving average parameter of the ARFIMA model. ARCH(1) and GARCH(1) are the volatility clustering parameters of the FIGARCH model. The key parameters of interest are ξ and d, which are the long memory estimates for ARFIMA and FIGARCH respectively.

The long memory parameter ξ for return series is insignificant among 9 of 11 countries. Although for Germany and Finland there exist some evidence for long memory,

[15] Return series used at previous sections are multiplied with 100 for simplify the convergence of likelihood.

these evidences are statistically weakly significant. The estimates of the ARFIMA model confirm the findings of the previous section, which concluded that return series do not exhibit long memory. Furthermore, for 6 of the 11 countries, short memory components such as AR(1) and MA(1) are significant, where Germany, Finland and the Netherlands are among these significant countries. This implies that previous evidence of long memory indicated by semi-parametric methods for return series is mainly driven by the short memory components. Parametric estimation reveals that there is actually no evidence of long memory for returns of Germany, Finland and the Netherlands.

In order to analyze the volatility of the returns series, the FIGARCH memory parameter d is relevant. Unlike return series, volatility of returns exhibits long memory among the majority of the countries. Confirming the results of semi-parametric estimates, there is no evidence of persistent volatility for Austria and France. As presented above, the evidence of persistency in volatility for the Netherlands is rather weak and is not present among most of the ordinates for the GPH and MLR. Using parametric estimates we found statistically very weak effects for the Netherlands, which indicates there is no persistence in volatility for this country. This weak effect could most probably be explained with additional covariates employed for the mean equation of variance.

Contrary to the semi-parametric estimates, the parametric estimates show no long memory effects for Germany. Interestingly, it is observed that both of the short memory components are significantly different from zero at conventional levels, implying long memory evidence of the previous section was a result of short memory components in the series. Except for Austria, France, Germany and the Netherlands there is evidence of long memory for the rest 7 out of 11 countries at all significance levels. These findings are further validation of the previous section's results, which indicate evidence of long memory for volatility of returns.

The coefficient of long memory coefficient is highest for Greece, followed by Portugal and Ireland. This result may indicate that the countries with highest sovereign debt risk are characterized by the most persistent behavior in volatility. Not only for these 3 countries but also for Italy, Spain and Belgium there is strong evidence of long memory for volatility series, indicating that there is a strong relation between sovereign debt risk and the persistence of volatility shocks. The only exception where sovereign risk is low but evidence of long memory is given is Finland, where the persistence may be an outcome of some spillover effects from other countries.

All in all, our results reveal that there is no evidence of long memory for return series for any of the euro area countries investigated. Despite the high volatility and unexpected shocks in sovereign CDS markets, the pricing mechanisms function efficiently. Moreover, relatively stable economies of the euro area such as Austria, France, Germany and the Netherlands do not exhibit persistent behavior also in volatility of CDS returns. This finding implies that the sovereign riskiness of these countries is still at a sustainable level, and investing in the sovereign bonds of these countries comprises of fewer risk factors. More indebted economies of the euro area such as Greece, Ireland, Belgium, Portugal, Italy and Spain, exhibit persistency in risk behavior. The increased global risk aversion and lack of certainty regarding future sovereign debt market conditions have caused an increase in sovereign CDS volatility, which was shown to be an ideal measure of sovereign risk. Our results reveal that, in addition to increased volatility, the effect of these volatility patterns as well as shocks die out very slowly and persist for long periods. This fact has various implications for modeling inferences to reduce volatility and improve liquidity in the sovereign debt market.

6 Conclusion

This article has addressed the question whether there is long memory behavior of the return and the volatility of the return series for sovereign CDSs of 11 euro area countries. We test the price efficiency and country risk of these entities for the crisis period. In doing this, semi-parametric methods and parametric estimation techniques that allow dual-memory analysis are employed. Our results point out that, despite the financial crisis and concerns regarding sovereign indebtedness for euro area countries, the price discovery processes function efficiently for sovereign CDS markets. This implies that speculative returns using sovereign CDSs through different channels would not be given for the period of interest. On the other hand, the persistence of riskiness of sovereign indebtedness is an issue for the majority of euro area countries. Our results indicate that the more stable economies of euro area such as Austria, the Netherlands, Germany and France are not prone to long memory of sovereign CDS volatility. Unlike these countries, sovereign CDSs of highly indebted economies such as Greece, Ireland, Portugal, Italy, Spain and Belgium exhibit long memory behavior. This finding points out that these countries show persistent country risk. Exhibiting long memory behavior, Finland most probably suffers from spillover effects. Our study has shed light on the time series properties of sovereign CDSs of the euro area countries about which little is known. Future research that examines different term structures of sovereign CDSs as well as different base currencies would be an interesting extension to this study.

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Figure 1: Sovereign CDS spreads for 11 euro area economies: 10-year maturity mid in basis points.

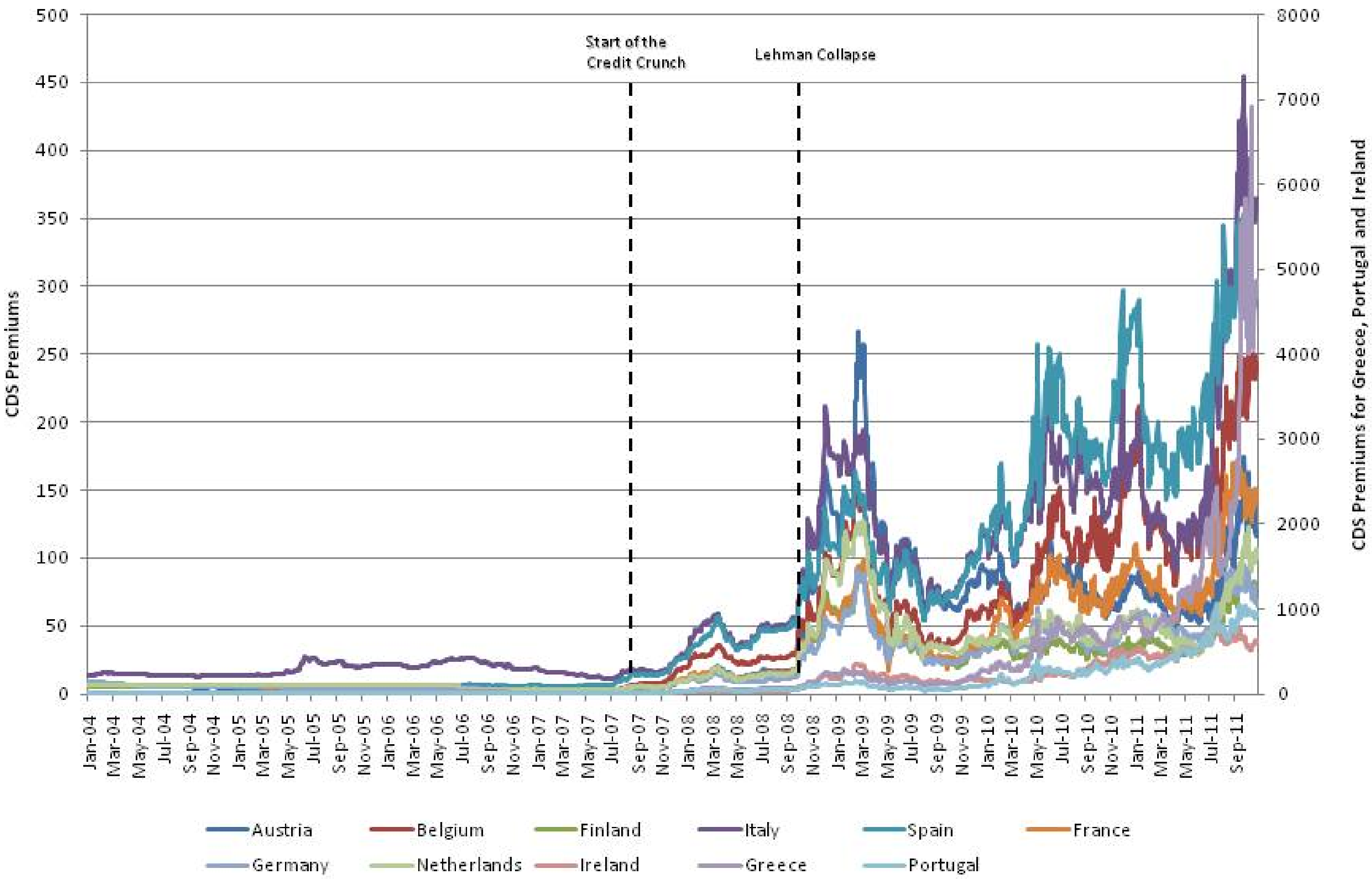

Table 1: Summary Statistics of CDS Levels January 2004-August 2007

	Mean	Median	Min	Max	SD	Skewness	Kurtosis	J-B	N
Austria	3.96	3.95	2.37	5.24	0.80	-0.14	2.06	37**	938
Belgium	4.79	4.72	3.16	6.41	0.83	0.32	2.31	35**	938
Italy	17.66	15.89	11.35	27.76	4.32	0.48	1.85	87**	938
Spain	5.59	5.47	4.42	10.93	0.90	2.36	12.73	4569**	938
Portugal	10.86	10.15	7.37	17.0	2.71	0.57	1.97	92**	938
France	4.39	4.11	2.51	7.33	1.23	0.65	2.62	73**	938
Germany	4.62	4.89	2.32	8.44	1.42	0.61	3.43	66**	938
Greece	19.10	15.94	10.63	29.84	5.47	0.31	1.50	103**	938
Ireland	4.99	5.47	2.49	6.93	1.29	-0.53	1.85	94**	919
Finland	2.79	2.79	2.03	3.63	0.54	0.04	1.26	42**	331
Netherlands	2.92	2.85	2.36	3.96	0.35	0.87	3.02	37**	292

This table presents the descriptive statistics of the CDS levels employed in our analysis. SD indicates standard deviation. J-B denotes Jarque-Bera (1980) normality test statistic which has a chi-square distribution with 2 degrees of freedom. * and ** denote significance at 5% and 1% level respectively.

Table 2: Summary Statistics of CDS Levels August 2007-October 2011

	Mean	Median	Min	Max	SD	Skewness	Kurtosis	J-B	N
Austria	68.73	69.37	3.59	266.38	46.92	0.86	4.70	268**	1099
Belgium	80.12	66.00	5.02	254.43	56.15	0.87	3.33	142**	1099
Italy	118.99	113.93	15.51	454.69	78.00	1.35	5.65	656**	1099
Spain	124.68	107.31	10.57	352.65	82.07	0.59	2.46	77**	1099
Portugal	210.51	100.03	12.55	1049.69	236.67	1.74	5.49	841**	1099
France	52.04	49.20	4.22	169.41	36.31	0.81	3.45	130**	1099
Germany	35.46	36.14	4.14	95.25	21.12	0.41	2.74	34**	1099
Greece	568.97	233.08	15.56	6918.56	936.84	3.66	18.67	13692**	1099
Ireland	233.42	177.97	5.50	1050.47	202.98	0.99	3.34	183**	1099
Finland	32.66	31.85	3.44	93.3	19.48	0.92	3.72	179**	1099
Netherlands	42.35	39.37	3.56	126.67	27.62	0.92	3.62	172**	1099

This table presents the descriptive statistics of the CDS returns employed in our analysis. SD indicates standard deviation. J-B denotes Jarque-Bera (1980) normality test statistic which has a chi-square distribution with 2 degrees of freedom. * and ** denote significance at 5% and 1% level respectively.

Table 3: Summary Statistics of CDS Returns January 2004-August 2007

	Mean	Median	Min	Max	SD	Skewness	Kurtosis	J-B	N
Austria	-0.0005	0.0000	-0.1187	0.1953	0.0183	1.15	28.96	26522**	937
Belgium	-0.0004	0.0000	-0.1192	0.1263	0.0129	0.47	31.58	31919**	937
Italy	0.0002	0.0000	-0.0593	0.1188	0.0128	2.02	21.17	13521**	937
Spain	0.0004	0.0000	-0.0785	0.0997	0.0143	0.71	13.66	4517**	937
Portugal	0.0002	0.0000	-0.0634	0.1550	0.0140	3.57	39.26	53318**	937
France	-0.0006	0.0000	-0.1991	0.1327	0.0145	-1.80	55.87	109639**	937
Germany	-0.0008	0.0000	-0.1761	0.1761	0.0253	-0.09	17.78	8532**	937
Greece	0.0001	0.0000	-0.0864	0.1452	0.0161	1.62	19.39	10902**	937
Ireland	-0.0001	0.0000	-0.1946	0.2885	0.0386	0.46	14.84	5384**	917
Finland	0.0000	0.0000	-0.3782	0.3134	0.0547	-0.22	18.99	3528**	330
Netherlands	0.0006	0.0000	-0.2218	0.3428	0.0386	2.04	29.96	9046**	291

This table presents the descriptive statistics of the CDS levels employed in our analysis. SD indicates standard deviation. J-B denotes Jarque-Bera (1980) normality test statistic which has a chi-square distribution with 2 degrees of freedom. * and ** denote significance at 5% and 1% level respectively.

Table 4: Summary Statistics of CDS Returns August 2007-October 2011

	Mean	Median	Min	Max	SD	Skewness	Kurtosis	J-B	N
Austria	0.0032	0.0004	-0.2701	0.4225	0.0527	0.94	12.1	3946**	1098
Belgium	0.0035	0.0007	-0.2281	0.2660	0.0516	0.22	7.06	763**	1098
Italy	0.0029	0.0011	-0.3705	0.2055	0.0450	-0.34	9.03	1687**	1098
Spain	0.0030	0.0005	-0.3331	0.2317	0.0467	-0.17	7.28	845**	1098
Portugal	0.0039	0.0015	-0.5271	0.3233	0.0566	-0.60	15.95	7736**	1098
France	0.0032	0.0006	-0.3807	0.5478	0.0640	0.63	14.23	5844**	1098
Germany	0.0025	0.0003	-0.3005	0.2626	0.0520	-0.16	6.63	607**	1098
Greece	0.0052	0.0031	-0.5602	0.3053	0.0522	-1.49	24.97	22486**	1098
Ireland	0.0043	0.0011	-0.3254	0.3809	0.0452	0.63	12.75	4419**	1098
Finland	0.0026	0.0000	-0.3137	0.5219	0.0610	0.91	12.14	3975**	1098
Netherlands	0.0029	0.0001	-0.3191	0.2992	0.0566	0.09	8.14	1212**	1098

This table presents the descriptive statistics of the CDS returns employed in our analysis. SD indicates standard deviation. J-B denotes Jarque-Bera (1980) normality test statistic which has a chi-square distribution with 2 degrees of freedom. * and ** denote significance at 5% and 1% level respectively.

Figure 2: Autocorrelation Functions August 2007-October 2011

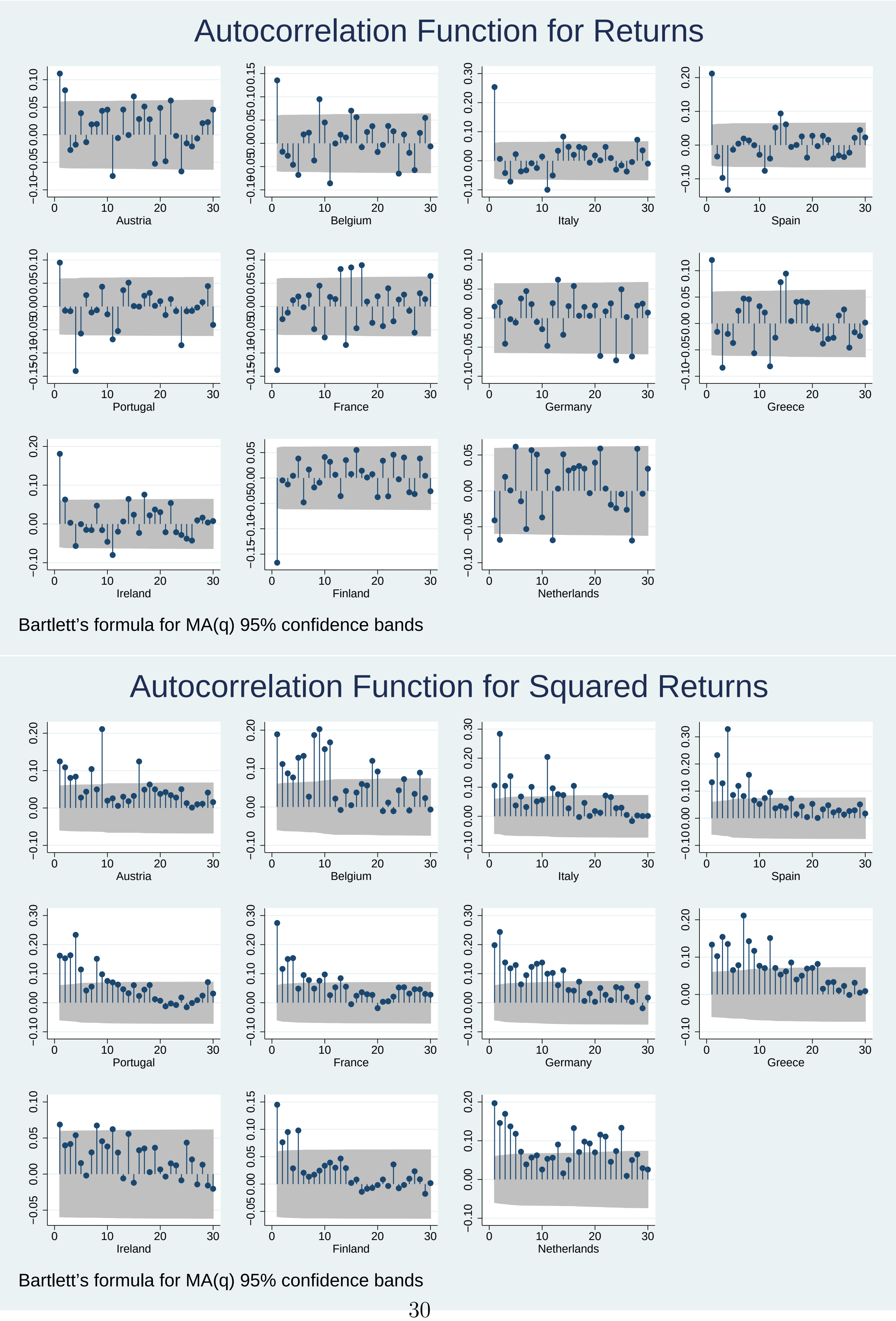

Table 5: Tests of Unit Root

	CDS Returns			**Squared CDS Returns**		
	DF-GLS	*P-P*	*KPSS*	*DF-GLS*	*P-P*	*KPSS*
Austria	-13.9**	-29.7**	0.115	-18.1**	-29.8**	0.320**
Belgium	-15.6**	-28.7**	0.085	-17.4**	-28.1**	0.157
Italy	-16.5**	-25.2**	0.090	-16.0**	-31.1**	0.104
Spain	-16.9**	-26.2**	0.039	-16.0**	-30.7**	0.196*
Portugal	-16.7**	-30.0**	0.041	-18.3**	-29.5**	0.590**
France	-11.1**	-38.3**	0.055	-13.4**	-25.8**	0.116
Germany	-10.4**	-32.5**	0.057	-8.9**	-28.5**	0.296**
Greece	-14.4**	-29.2**	0.079	-18.4**	-29.8**	0.278**
Ireland	-16.2**	-27.5**	0.085	-21.4**	-31.1**	0.085
Finland	-20.9**	-39.4**	0.090	-19.7**	-29.1**	0.237**
Netherlands	-12.8**	-34.6**	0.108	-14.6**	-28.3**	0.246**

Note: DF-GLS indicates the (Elliott and Stock (1996)) unit root test, P-P indicates (Phillips and Perron (1988)) unit root test and KPSS indicates the (Kwiatkowski et al. (1992)) test for stationarity. For DF-GLS and KPSS, max number of lags are determined using Schwert criterion which is 21. For P-P, in order to calculate standard errors Newey-West criterion is employed, which is 6. Critical value at 1% for DF-GLS is -3.480, where it is -3.430 for P-P and 0.216 for KPSS. * and ** denote significance at 5% and 1% level respectively.

Table 6: Long Memory for post 9 August 2007

	GPH						MLR					
Return Series												
	m= 0.5	t-val	m= 0.55	t-val	m= 0.60	t-val	m= 0.5	t-val	m= 0.55	t-val	m= 0.60	t-val
Austria	0.173	1.31	0.176	1.65	0.127	1.45	0.159	1.47	0.170	1.94	0.122	1.75
Belgium	0.239	1.81	0.192	1.80	0.084	0.96	0.211	1.45	0.173	1.53	0.072	0.84
Italy	0.193	1.46	0.135	1.27	0.012	0.13	0.244	1.78	0.170	1.51	0.039	0.42
Spain	0.118	0.90	0.067	0.63	-0.035	-0.40	0.080	0.56	0.030	0.29	-0.072	-0.86
Portugal	-0.002	-0.02	-0.014	-0.13	-0.057	-0.65	0.100	0.70	0.059	0.55	-0.004	-0.05
France	0.165	1.25	0.189	1.77	0.140	1.59	0.366**	5.08	0.349**	4.61	0.265**	3.61
Germany	0.102	0.77	0.149	1.39	0.115	1.31	0.330**	3.59	0.329**	3.64	0.252**	3.20
Greece	0.115	0.87	0.182	1.70	0.059	0.68	0.115	0.96	0.182	2.00	0.061	0.87
Ireland	0.181	1.37	0.233*	2.18	0.073	0.83	0.166	1.22	0.219	1.78	0.061	0.60
Finland	0.194	1.47	0.243*	2.28	0.150	1.71	0.602**	6.52	0.561**	6.43	0.401**	5.23
Netherlands	0.178	1.34	0.236*	2.21	0.108	1.23	0.505**	5.02	0.507**	6.07	0.319**	3.81
Squared Return Series												
	m= 0.5	t-val	m= 0.55	t-val	m= 0.60	t-val	m= 0.5	t-val	m= 0.55	t-val	m= 0.60	t-val
Austria	0.223	1.69	0.163	1.52	0.121	1.38	0.238	1.32	0.175	1.38	0.125	1.34
Belgium	0.294*	2.22	0.328**	3.07	0.375**	4.26	0.322**	2.79	0.349**	3.76	0.389**	5.40
Italy	0.241	1.83	0.278**	2.60	0.264**	3.00	0.272**	2.53	0.300**	3.77	0.279**	4.36
Spain	0.106	0.80	0.110	1.03	0.247**	2.81	0.218	1.98	0.196**	2.53	0.309**	3.97
Portugal	0.170	1.29	0.242*	2.27	0.264**	3.01	0.159	1.15	0.230*	2.19	0.253**	3.04
France	0.169	1.28	0.147	1.38	0.207*	2.36	0.176	1.21	0.152	1.39	0.211*	2.47
Germany	0.259	1.96	0.320**	2.99	0.276**	3.14	0.314*	2.40	0.357**	3.55	0.305**	4.07
Greece	0.317*	2.40	0.395**	3.70	0.416**	4.73	0.305**	3.92	0.384**	5.83	0.405**	5.60
Ireland	-0.107	-0.81	0.110	1.03	0.060	0.68	0.163	1.49	0.305**	2.81	0.213*	2.52
Finland	0.045	0.34	0.141	1.32	0.079	0.90	0.045	0.31	0.141	1.12	0.079	0.86
Netherlands	0.297*	2.25	0.220*	2.06	0.160	1.83	0.261*	2.20	0.191	2.01	0.138	1.78

Note: * and ** denote significance at 5% and 1% level respectively. Time series for each country contain 1098 data points. m represents the power values employed, which are $T^{0.5}$,$T^{0.55}$ and $T^{0.60}$ that correspond to 33, 47 and 67 ordinates.

Table 7: Long Memory for Post Lehman Period

	GPH						MLR					
Return Series												
	m= 0.5	t-val	m= 0.55	t-val	m= 0.60	t-val	m= 0.5	t-val	m= 0.55	t-val	m= 0.60	t-val
Austria	0.080	0.55	0.160	1.34	0.070	0.71	0.105	0.92	0.157	1.35	0.069	0.77
Belgium	0.069	0.47	0.085	0.72	-0.057	-0.58	0.199	1.27	0.177	1.36	0.003	0.03
Italy	0.006	0.04	-0.018	-0.15	-0.168	-1.72	0.011	0.08	-0.001	-0.01	-0.149	-1.72
Spain	-0.193	-1.32	-0.151	-1.26	-0.241	-2.46	-0.003	-0.02	-0.015	-0.10	-0.148	-1.35
Portugal	-0.141	-0.97	-0.048	-0.40	-0.113	-1.15	-0.009	-0.11	0.060	0.68	-0.018	-0.21
France	-0.048	-0.33	-0.040	-0.34	-0.135	-1.39	0.234	1.96	0.211*	2.19	0.081	1.09
Germany	-0.085	-0.58	-0.040	-0.34	-0.058	-0.60	0.249	2.03	0.202*	2.09	0.115	1.35
Greece	-0.024	-0.17	-0.002	-0.02	-0.090	-0.92	0.006	0.04	0.014	0.12	-0.080	-0.85
Ireland	0.070	0.48	0.088	0.74	-0.033	-0.34	0.069	0.55	0.087	0.82	-0.034	-0.38
Finland	0.104	0.71	0.151	1.27	0.114	1.16	0.534	3.22	0.443**	3.50	0.281*	2.53
Netherlands	0.23	1.60	0.195	1.63	0.048	0.49	0.604	3.46	0.421**	3.12	0.179	1.59
Squared Return Series												
	m= 0.5	t-val	m= 0.55	t-val	m= 0.60	t-val	m= 0.5	t-val	m= 0.55	t-val	m= 0.60	t-val
Austria	0.311	2.13	0.270*	2.26	0.236*	2.41	0.336**	3.19	0.294**	3.47	0.243**	3.43
Belgium	0.365**	2.50	0.346**	2.90	0.418**	4.27	0.427**	3.06	0.392**	3.90	0.446**	5.01
Italy	0.155	1.06	0.190	1.59	0.143	1.47	0.287	1.93	0.303**	2.72	0.236**	2.86
Spain	0.162	1.11	0.220	1.84	0.274**	2.81	0.275**	3.31	0.306**	4.39	0.343**	5.48
Portugal	0.141	0.97	0.239*	2.00	0.240*	2.46	0.209	1.58	0.286**	2.83	0.281**	3.47
France	0.131	0.90	0.200	1.68	0.309**	3.16	0.195	1.94	0.244*	2.54	0.347**	3.28
Germany	0.266	1.82	0.339**	2.84	0.362**	3.70	0.213	1.83	0.289**	2.86	0.318**	3.80
Greece	0.308*	2.11	0.366**	3.06	0.332**	3.40	0.318*	2.23	0.373**	3.39	0.338**	3.99
Ireland	-0.018	-0.12	0.099	0.83	0.072	0.74	0.165	1.49	0.241**	2.78	0.176**	2.46
Finland	0.084	0.58	0.084	0.70	0.042	0.43	0.032	0.16	0.046	0.32	0.015	0.15
Netherlands	0.413**	2.83	0.235*	1.97	0.188	1.93	0.421**	3.11	0.237*	2.05	0.186*	2.11

Note: * and ** denote significance at 5% and 1% level respectively. Time series for each country contain 887 data points. m represents the power values employed, which are $T^{0.5}$,$T^{0.55}$ and $T^{0.60}$ that correspond to 30, 42 and 59 ordinates.

Table 8: Dual Memory

	ARFIMA(1,ξ,1)-FIGARCH(1,d,1)							
	μ	ξ	$AR(1)$	$MA(1)$	ω	d	$ARCH(1)$	$GARCH(1)$
Austria	0.193	-0.030	0.580***	-0.388**	3.605	0.367	-0.043	0.197
	(0.145)	(0.079)	(0.166)	(0.156)	(3.506)	(0.230)	(0.364)	(0.528)
Belgium	0.290*	0.013	0.198	-0.014	0.908	0.650***	0.268	0.743***
	(0.157)	(0.050)	(0.195)	(0.168)	(0.595)	(0.225)	(0.165)	(0.066)
Italy	0.235*	-0.012	0.197	0.077	1.301	0.398***	-0.010	0.203
	(0.124)	(0.058)	(0.209)	(0.184)	(1.322)	(0.128)	(0.476)	(0.563)
Spain	0.291**	-0.027	0.202	0.025	0.539	0.547***	0.268*	0.638***
	(0.116)	(0.052)	(0.189)	(0.164)	(0.428)	(0.147)	(0.113)	(0.129)
Portugal	0.419***	-0.145	0.486***	-0.155	0.854**	0.841***	-0.042	0.700***
	(0.082)	(0.099)	(0.153)	(0.114)	(0.425)	(0.126)	(0.097)	(0.075)
France	0.264	0.015	-0.265	0.344	2.351	0.363	0.425*	0.479**
	(0.160)	(0.046)	(0.319)	(0.290)	(1.722)	(0.243)	(0.234)	(0.213)
Germany	0.254	0.062*	-0.525**	0.482**	0.929	0.533	0.491**	0.737***
	(0.173)	(0.035)	(0.247)	(0.232)	(0.443)	(0.347)	(0.198)	(0.132)
Greece	0.397**	0.022	0.334*	-0.127	0.251*	0.938***	0.039	0.843***
	(0.145)	(0.073)	(0.177)	(0.149)	(0.152)	(0.239)	(0.162)	(0.105)
Ireland	0.327**	-0.010	0.463***	-0.232**	0.154	0.739***	0.427***	0.902***
	(0.151)	(0.072)	(0.149)	(0.118)	(0.134)	(0.181)	(0.138)	(0.050)
Finland	0.089	-0.052*	-0.939***	0.945***	3.505	0.714***	0.010	0.421
	(0.124)	(0.028)	(0.031)	(0.025)	(2.512)	(0.149)	(0.237)	(0.323)
Netherlands	0.304**	0.018	-0.733***	0.790***	4.423	0.525*	0.124	0.282
	(0.152)	(0.031)	(0.080)	(0.068)	(3.388)	(0.281)	(0.397)	(0.543)

Note: Robust standard errors are in parenthesis.*, ** and *** denote significance at 10%, 5% and 1% level respectively.