DEUTSCHE
BUNDESBANK
EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 08/2013

Sovereign default swap market efficiency and country risk in the eurozone

Yalin Gündüz
(Deutsche Bundesbank)

Orcun Kaya
(Goethe University Frankfurt)

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

ISBN 978–3–86558–893–7 (Printversion)
ISBN 978–3–86558–894–4 (Internetversion)

Non-technical summary

Credit default swaps (CDSs) are financial derivatives that are designed to transfer credit risk between banks, hedge funds or asset managers in a simple way: The buyer of the CDS is insured by the seller against the default of the underlying sovereign entity. The insurance premium (or "the CDS spread") of these CDSs written on sovereign entities have been seen as an important indicator of the economic health of a given country. This paper uses CDS spread changes as a measure for the informational efficiency of the sovereign markets and CDS spread volatilities as a proxy for persistency of country risks. Specifically, we test whether the dependence of consecutive observations dies out slowly over time ("long memory"). We firstly show that there is no evidence of such behavior of CDS spread changes for any of the 10 eurozone countries in our sample. This indicates that, despite the financial crisis and uncertainty of financial markets, price discovery processes satisfy the minimum requirements for a weak form of market efficiency for sovereign CDSs, i.e. recent CDS spread changes cannot be predicted with past CDS spread changes. Second, there is strong evidence of long memory for volatility patterns of spread changes for 6 out of 10 countries. Specifically, we observe Greece, Portugal, Ireland, Italy, Spain, and Belgium to demonstrate such behavior. This shows that economies in the eurozone, which have been particularly affected by the financial and the sovereign debt crisis, are exposed to high uncertainty risk not only for a short period but over a persistent horizon. Third, we illustrate that CDS volatility is causal to CDS levels, indicating that uncertainty in CDS markets translates into higher risk premia for sovereign risk. Finally, we highlight the existence of a comovement of CDS spread changes for all countries, which is more explicit among peripheral economies. Our results have implications on selecting sovereign risk measures: Increased global risk aversion and the uncertainty about future sovereign debt market conditions have caused an increase in sovereign CDS volatility, which has been shown to be a meaningful measure of sovereign risk.

Nicht-technische Zusammenfassung

Credit Default Swaps (CDS) sind Finanzderivate, die eine einfache Übertragung von Kreditrisiken zwischen Banken, Hedgefonds oder Vermögensverwaltern ermöglichen: Der Käufer des CDS wird vom Verkäufer gegen den Ausfall des zugrunde liegenden staatlichen Schuldners abgesichert. Die Versicherungsprämie (oder CDS-Prämie) von CDS auf Staatsanleihen gilt als wichtiger Indikator für die wirtschaftliche Lage eines Landes. Die vorliegende Arbeit untersucht anhand der Veränderungen von CDS-Prämien die Informationseffizienz der CDS-Märkte und anhand ihrer Volatilität die Persistenz von Länderrisiken. Insbesondere wird getestet, inwiefern die fortlaufenden Beobachtungen über die Zeit voneinander abhängig sind ("Langzeitgedächtnis"). Dabei wird gezeigt, dass sich im Hinblick auf die Entwicklung der CDS-Prämien in den zehn untersuchten Euro-Ländern keine Belege für ein "Langzeitgedächtnis" finden lassen. Dies deutet darauf hin, dass aktuelle Veränderungen von CDS-Prämien nicht mit Hilfe früherer Veränderungen von CDS-Prämien prognostiziert werden können. Folglich erfüllen die Preisbildungsprozesse an den Märkten für CDS auf Staatsanleihen trotz der Finanzkrise und der Unsicherheit an den Finanzmärkten die Mindestanforderungen für eine schwache Form von Markteffizienz. Andererseits gibt es bei sechs der zehn in der Stichprobe untersuchten Länder eine starke Evidenz für ein "Langzeitgedächtnis" im Hinblick auf die Volatilitätsmuster der Prämienentwicklung. Ein solches Verhalten ist speziell in Griechenland, Portugal, Irland, Italien, Spanien und Belgien zu beobachten; dies belegt, dass Länder des Euro-Währungsgebiets, die von der Finanz- und Staatsschuldenkrise besonders betroffen waren, nicht nur kurzfristig, sondern über einen längeren Zeithorizont hinweg dem Risiko hoher Unsicherheit ausgesetzt sind. Des Weiteren wird aufgezeigt, dass sich die Volatilität von CDS-Prämien kausal zum CDS-Niveau verhält, sodass sich Unsicherheit an den CDS-Märkten in höheren Risikoprämien für Länderrisiken niederschlägt. Abschließend wird aufgezeigt, dass die Veränderung der CDS-Prämien in allen untersuchten Ländern einen Gleichlauf aufweist, der bei den Peripherieländern deutlicher zutage tritt. Unsere Ergebnisse haben Implikationen für die Wahl geeigneter Messgrößen des Länderrisikos: Die gestiegene globale Risikoaversion und die Unsicherheit im Hinblick auf die künftige Entwicklung an den Staatsanleihemärkten haben einen Anstieg der an den Märkten für CDS auf Staatsanleihen beobachteten Volatilität bewirkt, die erwiesenermaßen eine aussagefähige Messgröße des Länderrisikos darstellt.

Bundesbank Discussion Paper No 08/2013

Sovereign Default Swap Market Efficiency and Country Risk in the Eurozone*

Yalin Gündüz† Orcun Kaya‡

Abstract

This paper uses sovereign CDS spread changes and their volatilities as a proxy for the informational efficiency of the sovereign markets and persistency of country risks. Specifically, we apply semi-parametric and parametric methods to the sovereign CDSs of 10 eurozone countries to test the evidence of long memory behavior during the financial crisis. Our analysis reveals that there is no evidence of long memory for the spread changes, which indicates that the price discovery process functions efficiently for sovereign CDS markets even during the crisis. In contrast, both semi-parametric methods and the dual-parametric model imply persistent behavior in the volatility of changes for Greece, Portugal, Ireland, Italy, Spain, and Belgium addressing persistent sovereign uncertainty. We provide evidence of causality from volatility in CDS prices to sovereign risk premiums for these peripheral economies. We furthermore demonstrate the potential spillover effects of spread changes among eurozone countries by estimating dynamic conditional correlations.

Keywords: Credit default swaps, long memory, sovereign risk, eurozone economies, FIGARCH, dynamic conditional correlation.

JEL-Classification: C22, C58, G01, G15

*The authors thank Jörg Breitung, Virginie Coudert, Klaus Düllmann, Robert Engle, Michael Haliassos, Jan Scheithauer, Marliese Uhrig-Homburg, participants of the *5th Financial Risks International Forum on Systemic Risk*, 2012 Paris; *Society for Nonlinear Dynamics and Econometrics 20th Symposium*, 2012 Istanbul; *Financial Management Association European Conference*, 2012 Istanbul; *International Finance and Banking Society Conference*, 2012, Valencia; *European Financial Management Association Conference*, 2012 Barcelona; *Econometric Society European Meetings*, 2012 Malaga; *CREDIT: 11th International Conference on Credit Risk Evaluation*, 2012 Venice; seminar participants at Goethe University Frankfurt and Deutsche Bundesbank for helpful comments and suggestions. We gratefully acknowledge the programme committee of *Society for Nonlinear Dynamics and Econometrics 20th Symposium* for being selected for the Gerald P. Dwyer Best Paper in Finance Award. The views expressed herein are our own and do not necessarily reflect those of Bundesbank.

†Yalin Gündüz is a Financial Economist at the Deutsche Bundesbank, Wilhelm Epstein Str. 14, 60431 Frankfurt, Germany. Phone: +49 (69) 9566-8163, Fax: +49 (69) 9566-4275, E-mail: yalin.gunduz@bundesbank.de.

‡Orcun Kaya (Contact author) is associated with the Goethe University Frankfurt, Department of Money and Macroeconomics, House of Finance, Grüneburgplatz 1, 60323, Frankfurt, Germany. Phone: +49 (69) 798 33827, E-mail: orkaya@wiwi.uni-frankfurt.de

Sovereign Default Swap Market Efficiency and Country Risk in the Eurozone

1 Introduction

Credit default swaps (CDSs) of sovereign debt have been the subject of 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 banks, hedge funds or asset managers in a simple way: The buyer of the CDS is insured by the seller against the default of the underlying sovereign entity. 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 sovereign risk.

It is now a known fact that many eurozone countries suffer from severe public deficit problems which they are trying to finance through sovereign indebtedness. For instance, Greece, being one of the most indebted countries in Europe, has a public debt level equivalent to 113% of that 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, the spread changes and volatility patterns are strongly linked to the efficient pricing of public debt and to the fluctuations in the perception of country risk (Longstaff et al. (2011), Grossman and Huyck (1988)).

This paper investigates the long memory properties of sovereign CDSs for 10 eurozone countries. CDS spread changes and volatilities have been analyzed as a proxy for the informational efficiency of the sovereign markets and the persistence of uncertainty. All other things being equal, the long-memory behavior of sovereign CDS spread changes would imply strong predictability and an untrustworthy price discovery process where the most up-to-date information about the market perception of the sovereign CDSs is not priced correctly. This indeed could create arbitrage possibilities for the issuers of these products. On the other hand, as 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]

We also analyze the possibility that the CDS spread changes could be correlated among the 10 eurozone countries. A higher correlation among sovereign CDS markets of the eurozone economies would imply a more integrated structure. The evolution of the comovement of sovereign CDS markets as well as the magnitude of the correlations shed light on the spillover effects, which are especially important during crisis periods.

Our analysis follows a three-step process. We first test for long memory behavior for both CDS spread changes and squared changes employing different tests and robustness parameters. Specifically, we employ the log periodogram regression of Geweke and Porter-Hudak (1983) and the modified log periodogram regression of Phillips (2007) for different ordinate lengths. Second, we model the long memory of spread change and squared spread change series using a dual long memory model. The dual memory method, which is a combination of Granger and Joyeux (1980) ARFIMA and Baillie et al. (1996) FIGARCH models, allows us to estimate the long memory parameters of spread changes while simultaneously estimating their volatility. Third, we focus on the spillover effects by employing the dynamic conditional correlation model of Engle (2002) and by utilizing a two-stage estimation methodology.

Our main results can be summarized as follows: First, we have shown that there is no evidence of long memory behavior of CDS spread changes for any of the countries in our sample. This indicates that, despite the financial crisis and uncertainty of financial markets, price discovery processes satisfy the minimum requirements for a weak form of market efficiency for sovereign CDSs. On the other hand, there is strong evidence of long memory for volatility patterns of spread changes for 6 out of 10 countries. Specifically, we observe Greece, Portugal, Ireland, Italy, Spain, and Belgium to demonstrate such behavior, which shows that the troubled economies in the eurozone which experience

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

serious instability are exposed to high uncertainty risk not only for a short period but over a persistent horizon. Third, we illustrate that CDS volatility is Granger-causal to CDS levels, indicating that uncertainty in CDS markets translates into higher sovereign risk levels. Finally, we highlight the existence of a comovement of CDS spread changes for all countries, which is more explicit among less stable economies.

Our paper contributes to several strands of the literature. First and foremost, it extends the econometric literature on the time series properties of CDS markets. Specifically, we provide evidence of long memory properties for the volatility of sovereign CDS spread changes. Even though CDS prices appear to have increased tremendously after the crisis, we have shown that price discovery and information mechanisms still seem to be functioning properly. In the light of our results, we can argue that speculative actions using sovereign CDSs through hedge funds or banks are less likely. 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 persistent volatility patterns in local stock markets as well as in the bond markets. Finally, evidence on the comovement of sovereign CDS markets has important implications on risk diversification with respect to eurozone debt portfolios.

This paper is organized as follows. Section 2 introduces a brief definition of sovereign CDSs as well as the effects of long memory behavior on financial time series. This section emphasizes the importance of persistency patterns in sovereign CDS spread changes 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 CDS spread changes and squared changes. Section 5 applies parametric dual long memory models to spread changes and their volatility, while disentangling the short memory components. Section 6 analyzes the dynamic conditional correlations between the series. Section 7 details our conclusions.

2 Motivation

2.1 A Brief review of sovereign CDSs

CDSs are a class of credit derivatives designed to transfer the credit exposure of fixed income products or loans, triggered by credit events such as a default or failure to pay. In the case of default, the buyer of the CDS is compensated by the notional amount of the CDS by the seller. Given that a 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 a corporate CDS, bankruptcy is not a credit event for a sovereign CDS, given that there is no operable international bankruptcy court that applies to sovereign issuers.

Sovereign CDSs 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 another)
- Arbitrage trading (buy/sell government bonds vs sell/buy sovereign CDS)

The first of these reasons has been perhaps the most important motive for the use of sovereign CDS with the start of the crisis in global markets. The increasing sovereign indebtedness of eurozone countries has given rise to a serious possibility of contagion (Jorion and Zhang (2007), Longstaff (2010)). After the economic uncertainty in Greece,

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

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 the levels of credit default swaps (Dieckmann and Plank (2012)). Nevertheless, spread changes[3] mostly exhibit the properties of martingale differences, which is consistent with the efficient markets hypothesis (Tsay (2002)). While changes in a series indicate its performance, volatility of changes (i.e. squared changes) provides information regarding the riskiness of the relevant series. For instance, it is a well-known fact that a relationship exists between the expected risk premiums of stocks and their volatility (French et al. (1987)).

The long memory of spread changes has various implications. If the first differences of a time series display long-term dependence, current realizations are highly dependent on past realizations and the remote past can help predict future returns. This distortion in turn gives rise to the possibility of arbitrage 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 that prices on traded assets reflect all 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, derivatives pricing, and financial market regulation (Taylor (2000), Poon and Granger (2003) and Dark (2007)). Furthermore, 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

[3] We use the term *spread changes* instead of *spread returns* throughout the study, and distinguish the terminology from the stock market.

market participants. If there is evidence of persistent 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 spread changes and volatility matter?

Although there has been extensive literature on the long memory properties of stock market returns[4] as well as on the long memory properties of stock market volatility,[5] 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, we test how sovereign CDS volatility provides information on country risk. In their recent study Ericsson et al. (2009) provide evidence that equity volatility is significant in explaining CDS spread levels and spread changes. 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 economic upheavals (Belke and Gokus (2011)).

Recent empirical literature documents the significant relationship between volatility and sovereign risk. Hilscher and Nosbusch (2010) show that countries with more volatile fundamentals have higher sovereign bond spreads. Since CDSs are a more direct indicator of sovereign risk, it can be argued that a high CDS volatility could be positively related to the riskiness of the sovereign entity itself. Given the importance of CDS volatility patterns, understanding the persistency of volatility becomes vital as well.[6] The speed of forgetting large volatility shocks in financial markets is important for at least two reasons. First, persistent high volatility may imply a higher extent of sovereign risk, as we show later through causality tests. Second, a persistent volatility can be used to predict the

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

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

[6]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.

stability structure of future economic variables.

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 the observations of 10-year[7] senior sovereign CDSs for 10 European Union countries. All quotes are based on euro-denominated CDS contracts which are extensively traded in the market. The countries covered for the analysis are Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain, which are all members of the European Monetary Union and share the euro as their common currency.[8]

Figure 1 presents the sovereign CDS spread levels from January 2004 to October 2011.[9] Figure 1 clearly indicates that, prior to August 2007, the CDS spreads are broadly stable in almost all countries. However with the start of the credit crunch, all series start to fluctuate considerably and the spreads for all countries increase very sharply. Visual examination of Figure 1 reveals a clear difference between the series for the pre and post August 2007 periods which most probably address a structural change. An article on BBC News on 9 August 2009 entitled *"Timeline: Credit crunch to downturn"* mentions that:

[7]According to Dieckmann and Plank (2012), 10-year sovereign CDS contracts are more liquid than 5-year contracts. Our results remain robust when 5-year contracts are used.

[8]We have included the countries for which the euro-denominated spread information is available. Furthermore we also restrict our attention to the counties in which at least 95% of the data exhibit non-zero daily changes to avoid spurious evidence of long memory. For instance Finland is excluded from our analysis given that Finish data includes 5% zero changes (stale prices), while for Luxembourg only USD sovereign CDS spread information is available.

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

Defined as "a severe shortage of money or credit", the start of the phenomenon (financial crisis) has been pinpointed as August 9, 2007, when bad news from French bank BNP Paribas triggered a sharp rise in the cost of credit, and made the financial world realize how serious the situation was. On the same day, the Federal Reserve's Open Market Trading Desk put USD 24 billion into its banking system, whereas the European Central Bank in Frankfurt injected USD 130 billion into European institutions, and another USD 84 billion the following day. 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 markets for advanced economies were neither traded liquidly (Dieckmann and Plank (2012)) 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 10 countries both before and after the crisis. Concentrating on Table 1, it is seen that average spreads are as low as 2.9 basis points for the Netherlands, while as high as only 17 and 19 for Italy and Greece respectively. Even before the crisis, spreads in Greece, Italy and Portugal are much higher compared to all other eurozone countries. Low standard deviations among sampled countries highlight the minimal variation in spreads before the start of the crisis. Table 1 also presents 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.

Focusing on Table 2, it is evident that the mean values of CDS levels fluctuate tremendously after 9 August 2007. Among the 10 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 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 concomitant 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, which highlight the variability of spreads. For instance, Greece with a deviation of 936 basis points indicates a huge variation, 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, variation in Greece is 170 times more for the crisis period. Finally, for the crisis period, skewness and kurtosis values indicate higher peaks and fatter tails.

Table 3 and Table 4 present summary statistics for CDS spread changes.[10] Contrary to the levels in the pre-crisis period, the spread changes of 10 countries seem to be rather similar. For instance, not only mean spread changes but also minimum or maximum changes are close for almost all countries.[11] On the other hand, for the crisis period there are still substantial differences among the descriptives of the spread changes. For instance, the mean change in Greece is two times higher than in Germany, where minimum and maximum changes are very different, with a range of -0.56% (Greece) to %0.54 (France). Moreover, there are still huge variations of CDS spread changes when compared with the pre-crisis period. Distributional characteristics of spreads seem to show similarities with the change series before and after the crisis. For all countries, the distribution of spread changes is positively skewed with very long right tails. Finally, Jarque-Bera (J-B) statistics reject normality for all countries at the 1% level, indicating that there are significant departures from normality.

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

[11]The maximum and minimum value as well as standard deviation for the Netherlands differ somewhat from the rest of the sample for the pre-crisis period given that the sample of this country starts in June 2006.

All in all, the descriptives of the sovereign CDS spreads for both levels and changes 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.[12] Based on 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 spread changes and squared changes before pursuing further econometric analysis. To the best of our knowledge, very few studies deal with the time series properties of CDSs.[13] 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 (2012) find evidence of non-stationarity for 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 changes and squared changes of CDS spreads. If a series exhibits long memory structure, sample autocorrelations for changes or squared changes should tend to decay slowly and remain fairly large for long lags (Ding and Granger (1996), Bollerslev and Mikkelsen (1996)). Looking at Figure 2, it is evident that spread changes do not exhibit lag correlations with

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

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

distant observations.[14] In some cases the autocorrelation of the spread changes happens to be significant but disappears after the first lag. The rest of the lags are almost always within 95% confidence bands among all countries. The autocorrelation function of spread changes suggests no evidence of long memory.

Contrary to spread changes, the autocorrelation function of squared changes decays slowly and exhibits long memory behavior. In almost all countries other than Ireland, distant lags are outside 95% confidence bands. Especially for the Netherlands, Belgium and Greece, the autocorrelation bars are out of confidence bands until the 10th lag and the autocorrelation function of squared spread changes 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 a total of three different tests to both changes and squared changes. We utilize the modified Dickey-Fuller(DF-GLS) unit root test (Elliott and Stock (1996)), the Phillips-Perron(P-P) unit root test (Phillips and Perron (1988)) and the KPSS stationarity test (Kwiatkowski et al. (1992)). The null hypothesis of the KPSS test differs from the DF-GLS and P-P tests. The DF-GLS and P-P 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 assumes short memory under the null hypothesis. In this respect, the rejection of both unit root and stationarity tests signal the presence of long memory in the series of these countries (Lee and Schmidt (1996), Su (2003)).

Table 5 shows the results of these three tests for both spread changes and squared changes. For the spread changes of 10 countries, the DF-GLS and P-P tests reject the null of unit root, indicating that spread changes do not follow a unit root process and can be modeled or tested with standard methods. Similarly, squared spread changes do not exhibit unit root behavior either. Additionally the first lag of the KPSS test fails to reject

[14] 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 spread changes. The crisis period has longer lag effects for all countries for both spread changes and squared changes. Figures of the pre-crisis period are not included in the paper but are available upon request.

the null of stationarity for spread changes at the conventional level (%1), indicating that spread changes neither follow unit root behavior nor are non-stationary. On the other hand, for the squared changes, the first lag of the KPSS test rejects the hypothesis of stationarity for Austria, Spain, the Netherlands, Portugal and Germany. As mentioned 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.[15]

For a fractionally integrated process X_t of the form

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

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

[15]See Banerjee and Urga (2005) for a detailed discussion.

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

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 $\sqrt{T}$.[16]

For $|d| < \frac{1}{2}$, the DFT and periodogram are non-stationary. Given the economic upheavals in some 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 applying the estimator.

Both the GPH and MLR estimates are based on log-periodogram regressions that utilize the first T^λ frequency ordinates. In addition to 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).

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

4.2 Persistence after the start of the crisis

Table 6 shows the long memory tests for both spread changes and squared spread changes for the period after August 9, 2007. In the below subsections, the long memory properties will be analyzed separately.

4.2.1 Long memory of the spread changes

As seen from Panel A of Table 6, the GPH estimates show no significant evidence of a persistence of spread changes for 8 of the 10 countries. Utilization of different powers of the GPH shows that results are robust in terms of including more ordinates (i.e. inclusion of more ordinates does not change the results). For Ireland and the Netherlands there is weak evidence of long memory for the power value of 0.55 and no evidence even for higher power values.[17] 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 10 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 spread changes, implying that spread changes satisfy the requirement of weak form efficient markets hypothesis.

On the other hand, MLR estimates show statistically significant and consistent evidence of long memory for the Netherlands. Moreover, the estimated long memory coefficients for these two countries are higher than 0.5, indicating that the estimates of the MLR are more reliable compared to the GPH. As mentioned above, the evidence of long memory for the Netherlands could be due to short-term effects. We have shown through autocorrelation graphs that spread changes in neither of the countries show long memory

[17]Normally, it may be expected that the inclusion of more ordinates would increase the possibility of long memory effect.

behavior. Moreover, their spread changes 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. For these two countries, 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 spread changes

Panel B of Table 6 presents the long memory estimates for squared spread changes, which is a proxy for spread change volatility. Contrary to spread changes, for which the evidence of long memory is not present for many countries, there is evidence of long memory for squared spread changes 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 Austria. Across all power levels and for both GPH and MLR, evidence on persistence of volatility does not exist. There is weak statistically significant evidence for France for the highest power value (0.6) in both of the tests, implying that for France squared spread changes 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 spread changes 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 evident that Greece and Belgium have the highest fractional difference parameters among all specifications. This indicates that persistence of risk exhibits explosive behavior for these series.

Among the 10 countries, Greece has the highest public debt, followed by Italy and Belgium. All three of these 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. We will come back to linking persistent volatility patterns to sovereign risk in a latter section.

4.3 Persistence after the Lehman default

As mentioned by Granger and Hyung (2004), a linear process with structural breaks can mimic the 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 (2012) 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 Lehman default (September 15, 2008) as an alternative break point.

Confirming the results of the previous subsection where the break point was selected as August 9, 2007, spread changes exhibit very little evidence of long memory (Table 7, Panel A). In addition to the lack of persistence 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 three countries evidence of long memory for spread changes is rather implausible.

Contrary to spread changes, the evidence of long memory for squared spread changes becomes even more pronounced among all countries when the post-Lehman period is considered (Table 7, Panel B). 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 spread changes of CDS show little evidence of long memory, satisfying the minimum requirements for a weak form market efficiency. However, contrary to spread changes, as a result of increased uncertainty in sovereign 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 in 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 the persistence of risk.

5 Dual Persistence and Volatility Clustering

Usage of semi-parametric methods such as GPH or MLR is limited due to a number of drawbacks. First, application of these methods requires a choice of bandwidth parameters in order to find the ordinates. This is mostly non-trivial. Moreover, our results in Section 4 confirm that the bandwidth choice greatly affects the magnitude and significance of the fractional integration parameters. Second, if the data generating process exhibits short memory properties, semi-parametric methods are known to be biased (Agiakloglou et al. (1993), Banerjee and Urga (2005)). This is due to the fact that the short-term properties of the financial series are not taken into account while estimating the fractional differencing parameter in the two-step estimation procedure. As an outcome of this bias, long-term parameters could be contaminated by the presence of short-term components. In this section, we re-estimate the long memory evidence using parametric models to shed light on the long memory properties of CDS markets more precisely. Specifically, we employ the dual long memory ARFIMA-FIGARCH model.

5.1 ARFIMA-FIGARCH process

We first introduce the parametric methods to estimate the components of dual memory. The spread changes that correspond to the mean equation of the model are estimated using an ARFIMA model, whereas the conditional variance is estimated using a FIGARCH model. This estimation takes place jointly using the full maximum likelihood information.

ARFIMA Model

In order to model long memory of the spread changes, the ARFIMA(p, ξ, q) model, which was developed by Granger and Joyeux (1980), is employed. ARFIMA(p, ξ, q) with mean μ can be expressed as

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

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)).

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

By employing an ARFIMA-FIGARCH model we analyze the dynamic adjustments of both the mean and conditional variance of the sovereign CDS spread changes for 10 eurozone economies. In order to estimate the joint long memory model, the quasi-maximum likelihood method implemented by Laurent and Peters (2002) is used. Following Bollerslev and Mikkelsen (1996), we employ a truncation lag of 1000 for the fractional differencing operator. With the quasi-maximum likelihood method and truncation lag, the positivity constraints documented in Bollerslev and Mikkelsen (1996) are satisfied for all our specifications.

In order to avoid spurious short or long memory evidence, it is important to choose the appropriate lag length for ARFIMA and FIGARCH models. We employ Akaike and Schwarz information criteria for the model selection.[18] First we model an ARMA followed by an ARFIMA model for different lag selections with optimal lag lengths $p, q \leq 2$. Information criteria suggest alternating lag lengths for AR and MA components for different countries. For instance ARFIMA(2,ξ,1) transpired to be optimal for some countries, whereas ARFIMA(2,ξ,2) was preferable for others. In order to nest all countries in terms of optimal lag length, we employ ARFIMA(2,ξ,2) for the conditional mean equation. Meanwhile, for the implementation of GARCH or FIGARCH models it is common to allow for one lag for each ARCH and GARCH component (Brunetti and Gilbert (2000)). In this respect, we allow one GARCH and ARCH lag in our specifications.

In applications of GARCH(1,1) model, the sum of estimated GARCH parameters could be close to unity by pointing out an integrated GARCH(IGARCH) process. On the other hand, using Monte carlo simulations, Baillie et al. (1996) shows that financial data generated by long memory models may mimic IGARCH behavior if fractional integration

[18] The Schwarz criterion puts a heavier penalty on additional parameters and as a result encourages parsimonious models. When Akaike and Schwarz criteria indicate different outcomes, we opt for the less parsimonious model by Akaike criterion.

is not controlled. In this sense, before pursuing with the ARFIMA-FIGARCH model, we first examine the GARCH coefficients of the ARFIMA-GARCH model.[19] The sum of the GARCH coefficients proved to be very close to one for all the countries. For Austria, France, Germany and the Netherlands the sums are around 0.95, whereas for Belgium, Ireland, Italy and Spain they lie between 0.97 and 0.99. For Greece and Portugal, the sum is even more than one, implying that unconditional variance of the model does not exist. By virtue of the fact that the sum of the GARCH parameters is close to unity, we continue with the ARFIMA(2,ξ,2)-FIGARCH(1,d,1).

Table 8 shows the estimates of the dual memory model for 10 eurozone countries. 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 spread changes is insignificant among all countries. This finding with the ARFIMA model confirms the previous section, which concluded that spread changes do not exhibit long memory. For Belgium, Ireland and the Netherlands some of the short memory parameters are significant that might give rise to concerns about short term predictability on these markets. However, this might be due to the common factor problem of ARMA models.[20] Moreover, it is important to note that the beginning of our sample period comprise a number of null changes (constant CDS prices). This period of stable prices could also be the driving factor of the short memory effect. We further test any evidence of short memory by employing the heteroskedasticity-robust version of the Box-Pierce test Lo and MacKinlay (1989). Allowing for autocorrelation lags up to 10, the Q-statistic is never significant indicating that a weak form of market efficiency is satisfied.

In order to analyze the volatility of the spread changes, the FIGARCH memory parameter d is relevant. Unlike spread changes, volatility of changes 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, France and the Netherlands. Contrary

[19]For the sake of brevity, estimates are not reported but are available upon request from the authors.

[20]For instance, in the estimated model for the Netherlands both AR and MA parameters are significant and close to each other. This could be avoided by fractional differencing.

to the semi-parametric estimates, the parametric estimates show no long memory effects for Germany. Interestingly, it is observed that the GARCH coefficient is significantly different from zero at conventional levels, implying that long memory evidence of the previous section could be an outcome of short memory components in this series.

The coefficient of long memory is the highest for Greece. The series for Greece is almost characterized by an integrated GARCH model. Portugal and Ireland follow Greece in terms of the magnitude of the coefficients. This result may indicate that the countries with highest sovereign risk are characterized by the most persistent behavior in volatility. There is strong evidence of long memory for volatility series not just for these three countries but also for Italy, Spain and Belgium, indicating a potential relationship between sovereign risk and the persistence of volatility patterns.

At this point, it is worth highlighting the differences between GARCH and FIGARCH specifications. Excluding Ireland, ARCH parameters transpire to be insignificant for all countries, when fractional integration is allowed. Not only the ARCH but also the GARCH coefficients of Austria, France and the Netherlands become insignificant. The almost integrated GARCH behaviour of Italy (0.97) transpires to be an outcome of long memory process. On the other hand, for Belgium, Ireland, Portugal, Spain and Greece, there is also volatility clustering behavior addressed by significant GARCH coefficients in addition to the persistence patterns in volatility.

5.3 Granger causality tests

This section reports the results of Granger causality tests to provide evidence on the nature of the relationship between sovereign CDS volatility and country risk. To do so, we employ the methodology developed by Toda and Yamamoto (1995) to test the causality between sovereign CDS volatility and sovereign CDS levels as well as sovereign CDS changes. Their test is comparable with the χ_2 distributed test statistic and is robust to possible non-stationarity or cointegration. In order to reach the test statistic, first an estimate of conditional variance from ARFIMA-FIGARCH model is obtained. Second, the optimal lag p of the vector autoregression (VAR) is estimated using information criteria as AIC. Third, VAR of order $p^* = p + k$ is estimated where k is the maximum integration order of the system. Given that the order of integration cannot be greater than one, we utilize $k = 1$ in our application. Finally, Granger causality test is performed for the VAR equations where the null hypothesis is no causality between variables. Table 9 presents the results of 10 countries for three different lag lengths. We test for Granger causality at lag lengths equal to 5, 10 and the optimal lag p as described above.

Panel A of Table 9 reports the results of the causality test where the causality runs from sovereign CDS volatility to the sovereign CDS spread. Statistical significant effects are present for all countries excluding the Netherlands and Ireland. The causality evidence is highly significant for 7 countries and weakly significant for Belgium, for which only a single lag is significant at the 1% level. These results indicate that increases in uncertainty of sovereign CDS spreads raise the country risk itself and thus the required insurance for a possible default. The causality at higher lags (i.e. 10 days) indicates that the impact of uncertainty is also long-lasting. Panel B of Table 9 shows the causality that runs from sovereign CDS volatility to the sovereign CDS changes. Since the previous panel illustrates how high volatility is linked with higher spreads, high volatility also causes high spread changes. For 9 out of 10 countries, null hypothesis of the absence of causality is rejected at 1% statistical significance. This indicates that the uncertainty present in the series also implies higher spread changes in the series itself.

The results in this section demonstrate that the volatility of CDSs is linked with CDS levels and CDS spread changes. This implies that persistence patterns in uncertainty are associated with the sovereign risk structure of a given country. Having already demonstrated that some of the eurozone countries exhibit a significant d parameter, this section provides further evidence that this is an indication of country risk. In this sense, the results in the previous section depicting Greece, Italy, Ireland, Portugal, Spain and Belgium as having a significant fractional integration parameter imply a higher extent of risk in levels.

5.4 Model specification tests

It is important to test if the implemented ARFIMA-FIGARCH model is appropriate for the sovereign CDS data. To test for model misspecification we employ Box-Pierce statistics on raw (Q-statistic), squared (Q^2-statistic) standardized residuals and Residual-Based Diagnostic (RBD) of Tse and Tsui (2002) for conditional heteroskedasticity.

Table 10 presents the model misspecification tests for residuals of the ARFIMA-FIGARCH model. The null hypothesis of the Q- and the Q^2-statistic is that there is no serial correlation in lags of the standardized and squared standardized residuals. The Q- and the Q^2-statistic for up to 20 day lags fail to reject the null hypothesis at conventional levels that there is no serial correlation. The last two columns of Table 10 present the RBD test statistics which look at the presence of heteroskedasticity in the standardized residuals. The results indicate that the non-heteroscedasticity hypothesis is not rejected. Both of the test results confirm that our modelling scheme is appropriate for the sovereign CDS data.

5.5 Robustness checks

It is known that the majority of the financial time series tend to have fat tails which may distort the results of the GARCH type models. In this respect, we test the robustness of our modelling scheme to the tail behaviour of the data. In order to test this, we first allow for a generalized error distribution (GED) instead of a normal distribution in our estimation. Second, we winsorize our data for the highest and lowest extreme values.

The GED with degrees of freedom ϑ is a symmetric distribution that can be both leptokurtic and platykurtic depending on the degrees of freedom with $\vartheta > 1$. For $\vartheta = 2$, GED reduces to standard normal distribution where for $\vartheta < 2$, it has thicker tails than normal distribution. The first item in Table 11 presents the coefficients of long memory parameters of conditional volatility for which GED distribution is used. In our specification, we fix the degrees of freedom to 1.25 for all countries by allowing very thick tail behavior. As seen from the first line in the table, the magnitude of the d parameter is higher for Belgium, Italy and Spain, but lower for Greece, Ireland and Portugal. Nevertheless, the significance of the fractional integration parameter remains unchanged, implying robust behavior when thick tails are present.

In order to avoid contamination from outliers, a second approach could be to winsorize the extreme values. Unlike many other types of data, financial time series do not allow the trimming of extreme values since trimming results in gaps in the estimated series. In this respect, one can alternatively winsorize the extreme points by fixing positive or negative outliers to a specified percentile of the data. We set the data points higher than 0.995^{th} percentile and lower than 0.005^{th} percentile to the 0.995^{th} and 0.005^{th} percentiles respectively by modifying 1% of the data in total. The second item in Table 11 presents the coefficients of long memory parameters of conditional volatility for which winsorized data is used. This analysis also confirms that our results are robust and there is still evidence of long memory in volatility for Belgium, Greece, Ireland, Italy, Portugal and Spain.

5.6 Prediction performance

Jiang and Tian (2010) documented that forecast performance can be substantially improved by incorporating long memory models. We finally evaluate the out of sample forecast performance of ARFIMA-GARCH versus the ARFIMA-FIGARCH model for conditional volatility. To test the prediction performance, we employ different forecast error measures. Addressing the difference between the estimated and ex-post volatility,[21] the mean absolute error (MAE) and root mean squared error (RMSE) are utilized.

[21]Since true volatility is never observed, it is common to use $\sigma_t = (y_t - \bar{y})^2$, where $\bar{y}$ is the sample mean of y_t.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|(\hat{\sigma}_t - \sigma_t)| \tag{7}$$

$$RMSE = \frac{1}{T}\sum_{t=1}^{T}\sqrt{(\hat{\sigma}_t - \sigma_t)^2} \tag{8}$$

where σ_t presents the true volatility versus $\hat{\sigma}_t$ the estimated volatility. We also utilize the logarithmic loss function (LL) by Pagan and Schwert (1990) which penalizes inaccurate variance forecasts more heavily when σ_t is low.

$$LL = \frac{1}{T}\sum_{t=1}^{T}(ln(\hat{\sigma}_t) - ln(\sigma_t))^2 \tag{9}$$

Table 12 presents the forecast performance of estimated conditional volatilities for 10 countries with the GARCH and FIGARCH models. Our forecasts are out-of-sample predictions which correspond to a time two months after our estimation period. There are different contributions of the FIGARCH model to the forecasting. For most countries that exhibit no long memory behavior in volatility (Austria, Germany and the Netherlands) the prediction power of FIGARCH model is inferior to that of GARCH model. In this sense allowing for fractional integration introduces noise to the forecasts. On the other hand, for France, Italy, Ireland and Spain, allowing for fractional integration in volatility improves the forecast performance of the model. Excluding France, all the mentioned countries exhibit long memory behavior in volatility, which implies that the appropriate modelling may also have impact on prediction performance. The FIGARCH specification is dominantly superior for Greece and Portugal, not only with the lower MAE and RMSE but also with lower LL. This finding addresses the fact that for the countries where the long memory parameter is high or very close to unity, the forecasting performance of fractionally integrated models becomes much more accurate.

5.7 Implications

Overall, our results reveal that there is no evidence of long memory for spread changes for any of the eurozone countries investigated. Despite the high volatility and unexpected shocks in sovereign CDS markets, the pricing mechanism satisfies the minimum requirements for the weak form of price efficiency. On the other hand, increased global risk aversion and the lack of certainty regarding future sovereign debt market conditions have caused an increase in sovereign CDS volatility, which has been shown to be an ideal measure of sovereign risk. More stable eurozone economies such as Austria, France, Germany and the Netherlands do not exhibit persistent volatility behavior. These economies could be viewed as being free of persistent sovereign risk uncertainty. However, less stable eurozone economies such as Greece, Ireland, Italy, Portugal, Spain and Belgium exhibit persistent volatility patterns. Our results reveal that, in addition to increased volatility, the effect of these volatility patterns as well as the shocks entailed die out very slowly and persist for long periods in these less stable economies. Moreover, it can be inferred from causality tests that this volatility is linked to sovereign riskiness. This fact has various implications for modeling inferences to reduce volatility and improve liquidity in the sovereign debt market.

6 CDS Spread Change Spillovers

Given that eurozone economies are linked through the monetary union, it is important to study the spillover possibilities in terms of sovereign CDSs. In order to analyze the spillover effects of CDS spread changes we employ the dynamic conditional correlation (DCC) model of Engle (2002). The novelty of DCC method is that it addresses the dynamic correlation of two time series consistently using a two-step approach. Engle and Sheppard (2001) demonstrate that the log-likelihood of the DCC model can be written as the sum of a mean and volatility part in addition to a correlation part. First of all, univariate models which allow for ARFIMA type conditional mean and FIGARCH type variance specifications are estimated. Then, transformed residuals resulting from the first stage are used to compute conditional correlation estimators where the standard errors for the first stage parameters remain consistent.

The bivariate DCC model is formulated as;

$$H_t = D_t R_t D_t \tag{10}$$

$$D_t = diag(\sigma_{11t}^{1/2} \ldots \sigma_{NNt}^{1/2}) \tag{11}$$

$$R_t = diag(\theta_t)^{-1/2} \theta_t diag(\theta_t)^{-1/2} \tag{12}$$

$$\theta_t = (1 - \alpha - \beta)\overline{\theta} + \alpha \varepsilon_{t-1} \varepsilon_{t-1}^{'} + \beta \theta_{t-1} \tag{13}$$

where H_t represents the 2×2 variance-covariance matrix of a conditional multivariate normal mean zero process with innovations ε_t, σ_{ijt} representing the time varying standard deviation of a univariate FIGARCH process, and θ_t standing for the conditional variance-covariance matrix of residuals satisfying $\alpha + \beta < 1$. $\overline{\theta}$ is a 2×2 identity matrix with the non-diagonal entries equal to ρ.

Table 13 presents the unconditional correlation of the standardized residuals (ρ) of CDS spread changes for 10 eurozone countries. DCCs are generated following the univariate ARFIMA(2,ξ,2)-FIGARCH(1,d,1) estimation for all series. Consequently, pairwise DCC correlations are computed. A higher unconditional correlation implies a stronger co-movement as well as a more linked structure between countries. The coefficients evolve approximately between 40% and 60% in value. The smallest coefficient is observed between the Netherlands and Greece followed by the Netherlands and Ireland. Germany and France also show low correlations with Ireland, Greece and Portugal. This indicates that the less stable economies in the eurozone are least linked with the more stable economies in terms of correlation of the sovereign CDS. The highest coefficient is observed between Spain and Italy followed by Spain and Portugal. Moreover, Portugal has the highest unconditional correlation with Italy. This result indicates that the comovements of CDS spread changes for these three countries are highly integrated. Germany and

France exhibit the highest correlation coefficient with each other. In addition, they also exhibit high correlations with Austria, the Netherlands and Spain.

Table 13 reveals an interesting correlation pattern for the less stable economies of the eurozone. The magnitudes of correlation coefficients between Belgium, Italy, Ireland, Portugal, Spain and Greece are higher compared to the correlation coefficients of these countries with Austria, France, Germany and the Netherlands.[22] This result indicates that there is a higher spillover effect of CDS spread changes between less stable economies than more stable ones. For instance, Greece has the highest ρ coefficient with Italy and Spain, whereas Spain has the highest correlation with Italy and Portugal.

Table 14 and 15 present the estimates of α and β coefficients of Equation 13, respectively. The coefficient of α in Equation 13 captures the impact of recent comovements on the correlation while coefficient β captures the persistence in correlation patterns. As seen from Table 14, the impact of short term movements on the conditional correlation is insignificant for 32 out of 45 cases. The magnitude of the coefficient is higher than 10% only for two pairs, namely Spain and France, and Spain and Italy. For cases such as Greece and Netherlands, or Belgium and Portugal, they are as low as 2%. Contrary to the short terms movements, persistence in correlation dynamics is highly significant as can be seen from Table 15. In 40 out of 45 cases we observe a significant coefficient of β. Not only the significance but also the magnitudes of β coefficients are high. Observation of values mostly over 90% indicates that modelling the correlation structure dynamically would be the most appropriate methodology for analyzing the correlations of CDS spread changes.

For an illustration of the correlation patterns over time, Figure 3 shows the evolution of the conditional correlation between Greece and 4 other countries which are Germany, Italy, Spain and Portugal. The correlation coefficients are always positive and fluctuate around 0.5 for all specifications. As our sample corresponds to the crisis period, there are no major shifts for any of the pairwise correlations even for the post Lehman period.

[22] The only exception is between Greece and Ireland where the correlation coefficient is insignificant.

The highest jumps in DCC occur between Greece and Spain where the β parameter is the lowest among the four countries. On the contrary, the Greece/Italy and Greece/Portugal pairs that have the highest β exhibit a more stable correlation structure.

7 Conclusion

This article has addressed the question of whether long memory behavior is present in the spread changes and volatility of spread changes for the sovereign CDSs of 10 eurozone countries. We test the price efficiency and volatility persistence of these entities for the crisis period. To do this, semi-parametric methods and parametric estimation techniques that allow dual-memory analysis are employed. Our results indicate that, despite the financial crisis and concerns regarding sovereign indebtedness for eurozone countries, price discovery processes function efficiently for sovereign CDS markets. This implies that speculative returns evolving from sovereign CDSs as the sole trading instrument would be less likely for the period under review. Furthermore, persistence of volatility is an issue for the majority of eurozone countries. We show that the more stable economies of the eurozone such as Austria, the Netherlands, Germany and France are not prone to long memory of volatility. Unlike these countries, the sovereign CDS volatility of those economies such as Greece, Ireland, Portugal, Italy, Spain and Belgium, which have been particularly affected by the financial and sovereign debt crisis, exhibit long memory behavior with a causal link to sovereign CDS levels. Finally, by estimating dynamic conditional correlations, we demonstrate the potential spillover effects that exist among eurozone countries.

Our study has shed light on the time series properties of the sovereign CDSs of eurozone countries, about which little is known. Future research examining different term structures of sovereign CDSs as well as different base currencies would be an interesting supplement to this study.

References

Agiakloglou, C., P. Newbold, and M. Wohar (1993). Bias in an estimator of the fractional difference parameter. *Journal of Time Series Analysis 14*, 235–246.

Baillie, R. T., T. Bollerslev, and H. O. Mikkelsen (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics 74*, 3–30.

Banerjee, A. and G. Urga (2005). Modelling structural breaks, long memory and stock market volatility: An overview. *Journal of Econometrics 129*, 1–34.

Barkoulas, J., C. Baum, and N. Travlos (2000). Long memory in the Greek stock market. *Applied Financial Economics 10*, 177–184.

Belke, A. and C. Gokus (2011). Volatility patterns of CDS, bond and stock markets before and during the financial crisis: Evidence from major financial institutions. Ruhr Economic Papers 0243, Ruhr Bochum University.

Bollerslev, T. and H. O. Mikkelsen (1996). Modeling and pricing long memory in stock market volatility. *Journal of Econometrics 73*, 151–184.

Brunetti, C. and C. L. Gilbert (2000). Bivariate FIGARCH and fractional cointegration. *Journal of Empirical Finance 7*, 509–530.

Campbell, J. Y., M. Lettau, B. G. Malkiel, and Y. Xu (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance 56*, 1–43.

Cheung, Y.-W. and K. S. Lai (1993). A fractional cointegration analysis of purchasing power parity. *Journal of Business & Economic Statistics 11*, 103–112.

Crato, N. and P. J. F. de Lima (1994). Long-range dependence in the conditional variance of stock returns. *Economics Letters 45*, 281–285.

Cremers, M., J. Driessen, P. Maenhout, and D. Weinbaum (2008). Individual stock-option prices and credit spreads. *Journal of Banking & Finance 32*, 2706–2715.

Dark, J. (2007). Basis convergence and long memory in volatility when dynamic hedging with futures. *Journal of Financial and Quantitative Analysis 42*, 1021–1040.

Diebold, F. X. and A. Inoue (2001). Long memory and regime switching. *Journal of Econometrics 105*, 131–159.

Dieckmann, S. and T. Plank (2012). Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. *Review of Finance 16*, 903–934.

Ding, Z. and C. W. J. Granger (1996). Modeling volatility persistence of speculative returns: A new approach. *Journal of Econometrics 73*, 185–215.

Elliott, G. and J. H. Stock (1996). Efficient tests for an autoregressive unit root. *Econometrica 64*, 813–836.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics 20*, 339–350.

Engle, R. F. and K. Sheppard (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. Working Paper Series 8554, National Bureau of Economic Research.

Ericsson, J., K. Jacobs, and R. Oviedo (2009). The determinants of credit default swap premia. *Journal of Financial and Quantitative Analysis 44*, 109–132.

Fontana, A. and M. Scheicher (2010). An analysis of euro area sovereign CDS and their relation with government bonds. Working Paper Series 1271, European Central Bank.

French, K. R., W. G. Schwert, and R. F. Stambaugh (1987). Expected stock returns and volatility. *Journal of Financial Economics 19*, 3–29.

Geweke, J. and S. Porter-Hudak (1983). The estimation and application of long memory time series models. *Journal of Time Series Analysis 4*, 221–238.

Gil-Alana, L. (2006). Fractional integration in daily stock market indexes. *Review of Financial Economics 15*, 28–48.

Granger, C. and R. Joyeux (1980). An introduction to long-memory time series models and fractional differencing. *Journal of Time Series Analysis 1*, 15–29.

Granger, C. W. J. and N. Hyung (2004). Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. *Journal of Empirical Finance 11*, 399–421.

Greene, M. T. and B. D. Fielitz (1977). Long-term dependence in common stock returns. *Journal of Financial Economics 4*, 339–349.

Grossman, H. I. and J. B. V. Huyck (1988). Sovereign debt as a contingent claim: Excusable default, repudiation, and reputation. *American Economic Review 78*, 1088–1097.

Gündüz, Y., T. Lüdecke, and M. Uhrig-Homburg (2007). Trading credit default swaps via interdealer brokers. *Journal of Financial Services Research 32*, 141–159.

Gündüz, Y. and M. Uhrig-Homburg (2011). Predicting credit default swap prices with financial and pure data-driven approaches. *Quantitative Finance 11*, 1709–1727.

Hilscher, J. and Y. Nosbusch (2010). Determinants of sovereign risk: Macroeconomic fundamentals and the pricing of sovereign debt. *Review of Finance 14*, 235–262.

Jacobsen, B. (1996). Long term dependence in stock returns. *Journal of Empirical Finance 3*, 393–417.

Jiang, G. J. and Y. S. Tian (2010). Forecasting volatility using long memory and comovements: An application to option valuation under SFAS 123R. *Journal of Financial and Quantitative Analysis 45*, 503–533.

Jorion, P. (2000). *Value-at-risk: The New Benchmark for Managing Financial Risk.* New York: McGraw-Hill.

Jorion, P. and G. Zhang (2007). Good and bad credit contagion: Evidence from credit default swaps. *Journal of Financial Economics 84*, 860–883.

Kim, C. S. and P. C. Phillips (2006). Log periodogram regression: The non-stationary case. Technical Report 1587, Cowles Foundation for Research in Economics, Yale University.

Kwiatkowski, D., P. C. B. Phillips, P. Schmidt, and Y. Shin (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics 54*, 159–178.

Laurent, S. and J.-P. Peters (2002). G@rch 2.2: An Ox package for estimating and forecasting various ARCH models. *Journal of Economic Surveys 16*, 447–485.

Lee, D. and P. Schmidt (1996). On the power of the KPSS test of stationarity against fractionally-integrated alternatives. *Journal of Econometrics 73*, 285–302.

Lo, A. W. (1991). Long-term memory in stock market prices. *Econometrica 59*, 1279–1313.

Lo, A. W. and A. C. MacKinlay (1989). The size and power of the variance ratio test in finite samples. *Journal of Econometrics 40*, 203–238.

Longstaff, F. A. (2010). The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics 97*, 436–450.

Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics 3*, 75–103.

Mandelbrot, B. B. (1971). When can price be arbitraged efficiently? A limit to the validity of the random walk and martingale models. *The Review of Economics and Statistics 53*, 225–236.

Pagan, A. R. and G. W. Schwert (1990). Alternative models for conditional stock volatility. *Journal of Econometrics 45*, 267–290.

Phillips, P. C. (2007). Unit root log periodogram regression. *Journal of Econometrics 138*, 104–124.

Phillips, P. C. B. and P. Perron (1988). Testing for a unit root in time series regression. *Biometrika 75*, 335–346.

Poon, S.-H. and C. W. J. Granger (2003). Forecasting volatility in financial markets: A review. *Journal of Economic Literature 41*, 478–539.

Su, J. J. (2003). On the power of the multivariate KPSS test of stationarity against fractionally integrated alternatives. *Applied Economics Letters 10*, 637–641.

Taylor, S. J. (2000). Consequences for option pricing of a long memory in volatility. Technical report, Unpublished Manuscript, Department of Accounting and Finance.

Toda, H. Y. and T. Yamamoto (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics 66*, 225–250.

Tsay, R. S. (2002). *Analysis of financial time series*. John Wiley & Sons, Inc.

Tse, Y. and A. K. Tsui (2002). A multivariate garch model with time-varying correlations. *Journal of Business & Economic Statistics 20*, 351–362.

Tables and Figures

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

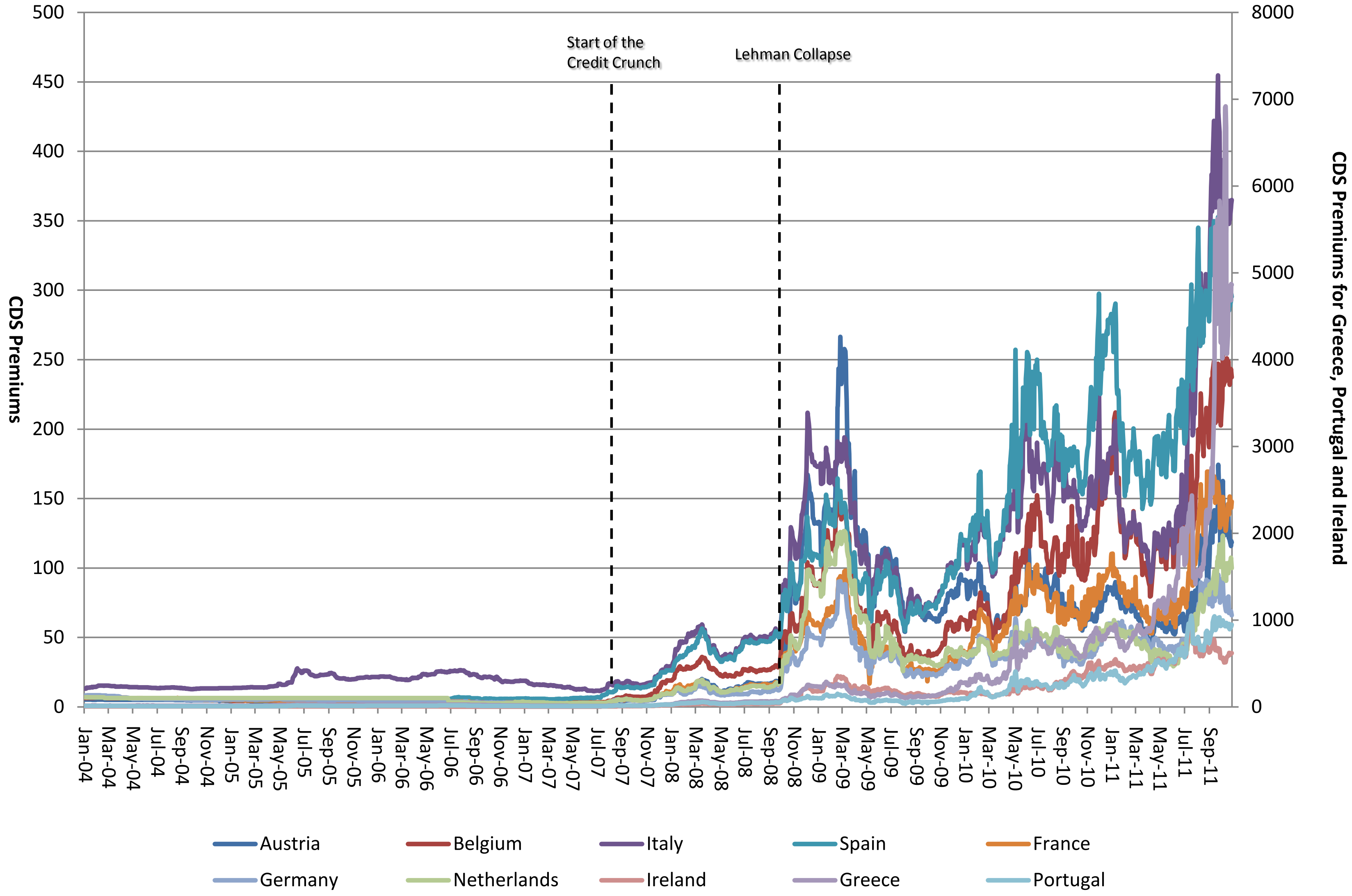


Table 1: Summary Statistics of CDS Levels January 2004-August 2007

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

This table presents the descriptive statistics of the CDS levels employed in our analysis. SD indicates standard deviation. * 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	N
Austria	68.73	69.37	3.59	266.38	46.92	0.86	4.70	1099
Belgium	80.12	66.00	5.02	254.43	56.15	0.87	3.33	1099
Italy	118.99	113.93	15.51	454.69	78.00	1.35	5.65	1099
Spain	124.68	107.31	10.57	352.65	82.07	0.59	2.46	1099
Portugal	210.51	100.03	12.55	1049.69	236.67	1.74	5.49	1099
France	52.04	49.20	4.22	169.41	36.31	0.81	3.45	1099
Germany	35.46	36.14	4.14	95.25	21.12	0.41	2.74	1099
Greece	568.97	233.08	15.56	6918.56	936.84	3.66	18.67	1099
Ireland	233.42	177.97	5.50	1050.47	202.98	0.99	3.34	1099
Netherlands	42.35	39.37	3.56	126.67	27.62	0.92	3.62	1099

This table presents the descriptive statistics of the CDS spread changes employed in our analysis. SD indicates standard deviation. * and ** denote significance at 5% and 1% level respectively.

Table 3: Summary Statistics of CDS Spread Changes 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
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 Spread Changes 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
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 spread changes 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

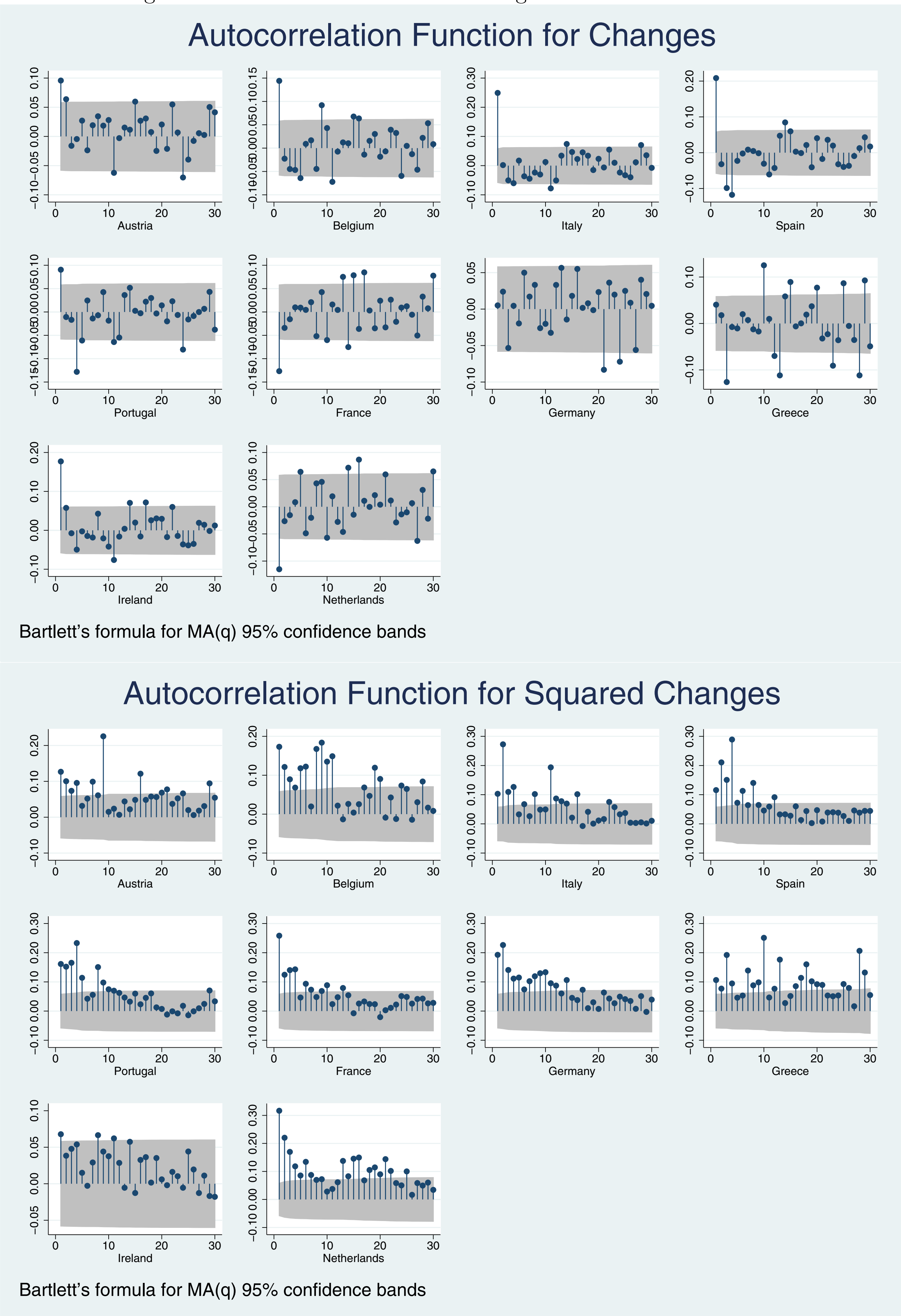


Table 5: Tests of Unit Root

	CDS Changes			**Squared CDS Changes**		
	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
Netherlands	-12.8**	-34.6**	0.108	-14.6**	-28.3**	0.246**

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					
Panel A	Spread Changes											
	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
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
Panel B	Squared Spread Changes											
	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
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

This table shows the long memory tests for spread changes and squared spread changes for the period after August 9, 2007. Panel A concentrates on spread changes, while Panel B illustrates the long memory estimates for squared spread changes. 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. * 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					
Panel A	Spread Changes											
	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
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
Panel B	Squared Spread Changes											
	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
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

This table shows the long memory tests for spread changes and squared spread changes for the period after the default of Lehman. Panel A concentrates on spread changes, whereas Panel B illustrates the long memory estimates for squared spread changes. 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. * 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(2,ξ,2)-FIGARCH(1,d,1)									
	μ	ξ	$AR(1)$	$AR(2)$	$MA(1)$	$MA(2)$	ω	d	$ARCH(1)$	$GARCH(1)$
Austria	0.184	-0.029	0.021	0.335	-0.175	-0.223	3.306	0.379	-0.003	0.255
	(0.145)	(0.079)	(0.314)	(0.223)	(0.326)	(0.218)	(3.843)	(0.239)	(0.464)	(0.642)
France	0.229	0.037	-0.006	-0.147	0.056	0.112	2.347	0.356	0.439	0.493*
	(0.175)	(0.056)	(0.631)	(0.122)	(0.645)	(0.104)	(1.721)	(0.203)	(0.230)	(0.199)
Germany	0.248	0.026	-0.422	0.037	0.437	0.019	0.945	0.559	0.460*	0.740**
	(0.149)	(0.045)	(0.365)	(0.322)	(0.364)	(0.323)	(0.429)	(0.316)	(0.193)	(0.122)
Netherlands	0.286*	-0.088	0.172	0.660**	-0.038	-0.668**	3.277	0.553	0.291	0.465
	(0.145)	(0.123)	(0.131)	(0.111)	(0.106)	(0.102)	(6.947)	(0.466)	(0.869)	(1.193)
Belgium	0.230	-0.157	1.244**	-0.271	-0.887**	-0.030	0.929	0.620**	0.285	0.739**
	(0.154)	(0.148)	(0.183)	(0.170)	(0.103)	(0.089)	(0.638)	(0.215)	(0.159)	(0.070)
Italy	0.220	-0.026	-0.1756	0.171	0.469**	-0.058	1.145	0.411**	0.063	0.295
	(0.121)	(0.055)	(0.103)	(0.115)	(0.110)	(0.095)	(1.362)	(0.159)	(0.493)	(0.607)
Ireland	0.313*	-0.010	-0.131	0.297**	0.369*	-0.167	0.158	0.746**	0.417**	0.905**
	(0.151)	(0.069)	(0.149)	(0.111)	(0.129)	(0.088)	(0.135)	(0.174)	(0.133)	(0.048)
Portugal	0.413**	-0.145	0.033	0.253	0.312	-0.121	0.891*	0.838**	-0.038	0.702**
	(0.083)	(0.105)	(0.228)	(0.169)	(0.244)	(0.097)	(0.452)	(0.126)	(0.098)	(0.076)
Spain	0.283	0.079	0.929	-0.615	-0.820	0.523	0.573	0.534**	0.251*	0.623**
	(0.182)	(0.225)	(1.489)	(1.265)	(1.848)	(1.410)	(0.460)	(0.127)	(0.112)	(0.132)
Greece	0.397**	0.026	-0.244	0.220	0.455	-0.110	0.198*	0.992**	0.008	0.876**
	(0.146)	(0.078)	(0.211)	(0.162)	(0.189)	(0.141)	(0.093)	(0.122)	(0.110)	(0.040)

This table presents the ARFIMA-FIGARCH model coefficients. μ is the estimated constant for the mean equation where ω is the constant for the variance equation. AR(1) and AR(2) are the autoregressive parameters, whereas MA(1) and MA(2) are the moving average parameters of the ARFIMA model. In the FIGARCH model, the volatility clustering is captured by ARCH(1) and GARCH(1). The key parameters of interest are ξ and d, which are the long memory estimates for ARFIMA and FIGARCH respectively. Robust standard errors are in parentheses. * and ** denote significance at , 5% and 1% level respectively. Spread change series used at previous sections are multiplied with 100 to simplify the convergence of likelihood.

Table 9: Granger Causality Tests

CDS volatility does not Granger-cause CDS spread

Days	AU	BE	GR	GER	FR	NT	IR	IT	PT	SP
5	55.64*	9.95	103.12*	21.49*	18.61*	4.76	6.14	76.86*	25.30*	35.47*
	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)	(0.31)	(0.29)	(0.00)	(0.00)	(0.00)
10	66.17*	27.88*	161.17*	28.35*	20.23	12.21	9.54	81.41*	33.82*	69.61*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.14)	(0.48)	(0.00)	(0.00)	(0.00)
opt	60.10*	10.08	475.05*	20.90*	16.51*	3.43	6.14*	76.86*	27.80*	65.87*
	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.33)	(0.29)	(0.00)	(0.00)	(0.00)

CDS volatility does not Granger-cause CDS spread changes

Days	AU	BE	GR	GER	FR	NT	IR	IT	PT	SP
5	133.67*	15.00	133.18*	14.05	55.20*	7.28	39.63*	68.23*	38.16*	21.92*
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
10	139.89*	47.83*	192.15*	20.76	66.56*	12.09	54.80*	66.19*	42.64*	66.19*
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)
opt	125.14*	13.11*	13.11*	11.86	54.99*	5.33	39.63*	59.67*	33.82*	59.67*
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)

This table presents the estimates of Granger-causality test. Days represent the number of lags to be included in the bivariate Granger causality test. p-values are presented in parentheses. * indicates significance at 1% level.

Table 10: Model Misspecification Tests

	Q-Statistics			Q^2-Statistics			RBD	
Country \ **Days**	5	10	20	5	10	20	2	5
Austria	1.44	5.20	17.35	0.66	4.12	7.10	0.10	0.64
	(0.23)	(0.52)	(0.36)	(0.88)	(0.85)	(0.99)	(0.95)	(0.99)
Belgium	4.38	7.46	20.58	2.10	4.21	7.07	0.75	2.57
	(0.04)	(0.28)	(0.20)	(0.55)	(0.84)	(0.99)	(0.69)	(0.77)
France	3.29	8.90	31.97*	0.55	1.17	2.26	0.27	0.59
	(0.07)	(0.18)	(0.01)	(0.91)	(1.00)	(1.00)	(0.87)	0.99
Germany	1.65	3.32	14.80	2.42	4.85	12.95	1.97	3.97
	(0.20)	(0.77)	(0.54)	(0.49)	(0.77)	(0.79)	(0.37)	(0.55)
Greece	0.35	4.56	21.15	1.58	2.98	12.09	0.35	1.13
	(0.56)	(0.60)	(0.17)	(0.66)	(0.94)	(0.84)	(0.84)	(0.95)
Ireland	3.50	9.08	29.78	4.53	7.85	17.38	-18.28	-18.12
	(0.06)	(0.17)	(0.02)	(0.21)	(0.45)	(0.50)	(1.00)	(1.00)
Italy	2.26	6.49	27.07	2.18	4.20	14.20	0.22	3.50
	(0.13)	(0.37)	(0.04)	(0.54)	(0.84)	(0.72)	(0.90)	(0.62)
Netherlands	3.58	14.79	28.88	1.25	2.09	5.48	0.85	1.02
	(0.06)	(0.02)	(0.02)	(0.74)	(0.98)	(1.00)	(0.66)	(0.96)
Portugal	3.16	13.74	29.78	1.22	4.36	8.99	0.33	1.65
	(0.08)	(0.03)	(0.02)	(0.75)	(0.82)	(0.96)	(0.85)	(0.90)
Spain	3.93	9.78	30.85*	0.80	1.23	4.34	-0.51	1.08
	(0.05)	(0.13)	(0.01)	(0.85)	(1.00)	(1.00)	(1.00)	(0.96)

This table presents the Q-statistic, Q^2-statistic for standardized residuals and Residual-Based Diagnostic test of Tse and Tsui (2002). Days present the number of lags being tested. p-values are presented in parentheses. * indicates significance at 1% level.

Table 11: Tests for the Tail Behavior

	AU	BE	FR	GE	GR	IR	IT	NE	PT	SP
GED	0.440	0.632*	0.462	0.603	0.923*	0.640*	0.608*	0.450	0.847*	0.646*
	(0.196)	(0.167)	(0.291)	(0.368)	(0.186)	(0.214)	(0.234)	(0.178)	(0.125)	(0.127)
Winsorize	0.326	0.560*	0.718	0.485	0.532*	0.814*	0.492*	0.478	0.675*	0.473*
	(0.143)	(0.150)	(0.217)	(0.164)	(0.136)	(0.131)	(0.260)	(0.248)	(0.213)	(0.192)

This table presents the conditional variance fractional integration parameter d. GED results are based on ARMA(2,2)-FIGARCH(1,d,1) model for ease of convergence. Winsorized extreme points correspond to 1% of the total data. * represents significance at 1%. Robust standard errors are presented in parentheses.

Table 12: Prediction Power of GARCH versus FIGARCH

	GARCH			FIGARCH		
	MAE	RMSE	LL	MAE	RMSE	LL
AU	66.37	107.00	11.79	86.91	114.50	13.84
BE	50.33	69.32	9.69	59.98	75.80	10.65
GRE	890.9	932.00	22.11	499.80	525.00	18.45
GER	46.55	55.07	7.85	65.05	71.53	10.17
FR	86.39	154.10	8.35	81.79	151.80	8.06
ITA	36.27	53.18	9.80	35.44	52.39	9.64
IR	33.07	37.33	16.91	30.67	36.01	16.25
NET	165.40	306.00	4.27	184.00	287.20	5.11
PT	114.60	119.40	20.65	65.53	66.92	16.89
SP	52.50	62.62	10.22	50.42	61.50	10.06

This table presents the out-of-sample forecast performance of conditional volatility estimated by ARFIMA-GARCH versus ARFIMA-FIGARCH models. Forecast period corresponds to 47 daily data points for November and December 2011, which are not used for estimation. All values are comparable to squared basis points.

Table 13: Unconditional Correlation

	AU	FR	GER	NET	BE	IT	IR	PT	SP	GRE
AU	1.000									
FR	**0.475**	1.000								
GER	**0.551**	**0.560**	1.000							
NET	**0.510**	**0.501**	**0.559**	1.000						
BE	**0.614**	**0.523**	**0.526**	**0.511**	1.000					
IT	**0.584**	**0.510**	**0.547**	**0.492**	**0.654**	1.000				
IR	**0.532**	**0.424**	**0.424**	**0.380**	**0.596**	**0.597**	1.000			
PT	**0.572**	**0.449**	**0.451**	**0.511**	**0.627**	**0.664**	**0.574**	1.000		
SP	**0.566**	**0.513**	**0.516**	**0.523**	**0.699**	**0.776**	**0.591**	**0.772**	1.000	
GRE	**0.483**	**0.435**	**0.430**	**0.368**	**0.514**	**0.609**	0.476	**0.559**	**0.585**	1.000

This table presents the unconditional correlation coefficients ρ of Equation 13. Correlation coefficients in bold are significant at 1%.

Table 14: Recent Comovements

	AU	FR	GER	NET	BE	IT	IR	PT	SP	GRE
AU	1.000									
FR	0.015	1.000								
GER	0.020	0.050	1.000							
NET	0.023	0.038	**0.029**	1.000						
BE	**0.096**	0.036	**0.056**	0.019	1.000					
IT	**0.094**	0.018	**0.017**	0.069	0.018	1.000				
IR	0.000	0.013	0.028	0.021	0.019	0.026	1.000			
PT	0.059	**0.024**	0.026	0.019	**0.019**	0.021	0.017	1.000		
SP	**0.071**	**0.135**	**0.051**	0.016	0.104	**0.116**	0.024	**0.056**	1.000	
GRE	0.001	0.054	0.040	**0.017**	0.023	0.017	0.025	0.021	0.103	1.000

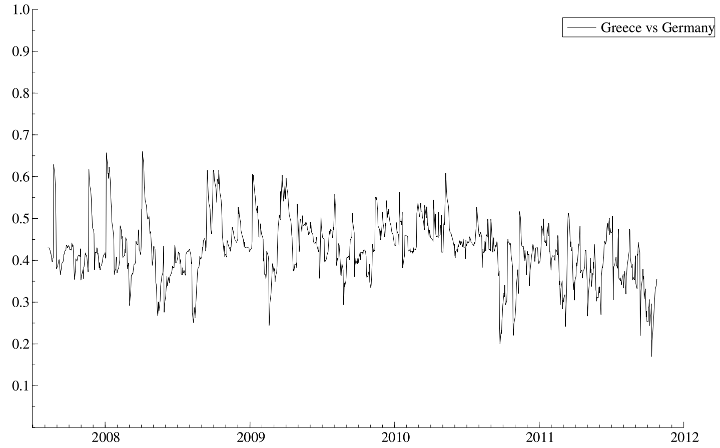
This table presents the recent comovement coefficients α of Equation 13. Coefficients in bold are significant at 1%.

Table 15: Persistent Comovements

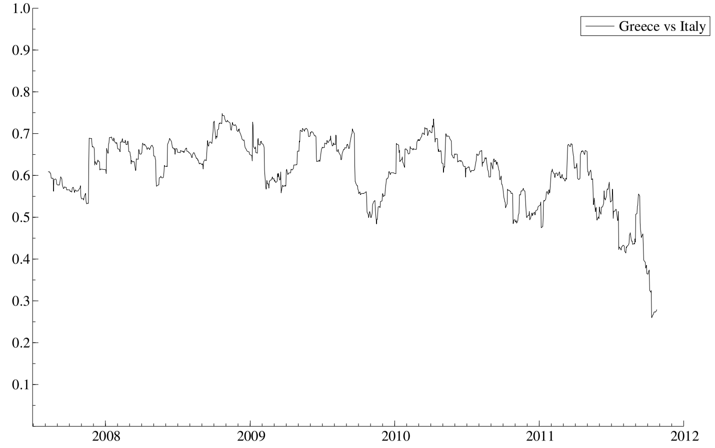
	AU	FR	GER	NET	BE	IT	IR	PT	SP	GRE
AU	1.000									
FR	0.515	1.000								
GER	**0.966**	**0.927**	1.000							
NET	**0.962**	**0.938**	**0.957**	1.000						
BE	0.453	**0.881**	**0.839**	**0.949**	1.000					
IT	**0.404**	**0.762**	**0.958**	**0.968**	**0.819**	1.000				
IR	0.760	**0.939**	**0.917**	**0.962**	**0.946**	**0.946**	1.000			
PT	0.000	**0.964**	**0.951**	**0.967**	**0.948**	**0.939**	**0.969**	1.000		
SP	**0.726**	0.355	**0.885**	**0.969**	**0.787**	**0.686**	**0.943**	**0.922**	1.000	
GRE	**0.984**	**0.854**	**0.826**	**0.972**	**0.906**	**0.970**	**0.964**	**0.947**	**0.649**	1.000

This table presents the persistent comovement coefficients β of Equation 13. Coefficients in bold are significant at 1%.

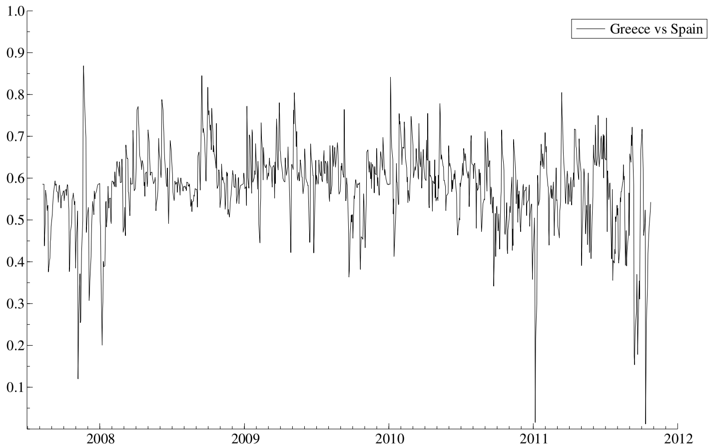
Figure 3: Selected Pairwise Dynamic Conditional Correlations for Greece



(a) Greece vs Germany



(b) Greece vs Italy



(c) Greece vs Spain

(d) Greece vs Portugal