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Influence of the Greek Crisis on the Risk Perception of European Economies

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Abstract

In the article the author analyses the impact of the Financial Crisis, especially the Greek fiscal one, on the sCDS prices in Europe. The aim of the article is to assess the ability of the sCDS premia to price the risk of countries before and during the Greek crisis. The author analyses sCDS premia of maturity 10 years together with the so called bond-spreads, i.e. the spreads between the countries' bond indexes and the risk free rate of the region (in our case it was the yield of German bonds of corresponding maturity - 10 years). The idea was to check whether there occurred any discrepancies in the risk valuation via the two measures, as a consequence of the Greek crisis. The data is taken daily and covers the period of 2008-2012. Based upon the results obtained in the research we conclude that the Greek crisis indeed influenced the relationships between the two measures of risk, however the degree of the influence was different in different countries. The relationships between the two measures of risk were totally broken only in the case of Greece, while in the other countries the relationships either were not distorted or had been broken already at the beginning of the financial crisis (2008/2009). The Greek problems were indeed reflected in volatilities of all analysed instruments; however triggering the credit event affected only Greek bonds dynamics.

Keywords: CDS, bond spread, Markov-switching models, GARCH models, volatility, financial crisis

JEL Classification: G01, G15, E4, F3

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1 Introduction

The aim of the research was to investigate the properties of the sovereign Credit Default Swaps (in short: sCDS) spreads in Europe in order to verify whether their properties changed as a consequence of the Greek crisis. The spreads were analysed together with the adequate bond spreads, i.e. the spread between the yield of a given bond and the risk-free rate of the region, which in our case was the yield of German bonds. The motivation of this approach is as follows. The sovereign CDS instruments can be treated as a kind of protection against the bankruptcy of the country. If investors buy a given country's bond, they can protect themselves against the situation of not receiving their interests and/or the payoff through entering the sovereign CDS contract. If the so called "credit event" is triggered, the investors obtain the payoff from the contract. On the other hand, if the risk of the bankruptcy in the country grows, the cost of lending money to such an entity should also grow, and consequently, the yield of the bonds issued by the country should increase (compared to the risk-free rate). Simultaneously, the cost of protection against the government's insolvency should also grow - and thus the price of the CDS contract. This suggests that the values of the two spreads should move in the same direction and have similar dynamics.

2 Greek crisis

Already at the beginning of 2010 Greek stability and credibility were put in question. As the situation was getting worse and worse, on April 23rd, 2010, the Greek government requested for activation of an EU/IMF bailout package. In consequence, four days later S&P lowered the rating of Greek sovereign debt to BB+. This decision caused the sharp growth of yields of the Greek bonds and the CDS premia. A while later Moody's and Fitch also downgraded Greece, which caused subsequent growth of the yields. This situation was stabilized after the announcement of the ECB that it would accept Greek bonds as collaterals, no matter of the Greek rating (May 3rd). On May, 1st, Greek government announced a series of austerity measures and asked for an EU/IMF loan package. The eurozone and the IMF agreed to a three-year loan of EUR 110 billion, on condition that the austerity package was implemented (Nelson et al., 2011). Immediately, the ratings of Greece were cut. Although the austerity package was implemented and the loan given, the crisis deepened in following months. The austerity measures taken by the Greek government led to strikes and did not improve the situation. A year later, in May 2011 it became clear that it would be hard for Greece to make its fiscal goals (Traynor, 2011). Again, in June 2011 the credit rating agencies downgraded the rating of Greek sovereign bonds to CCC. The government plans to implement further spending cuts were met with anger and strikes. Eventually, the new austerity package was approved, as well as the next loan package (June 27, 2011).

In July 2011 the European Financial Stability Facility was created (Nelson et al. 2011), which could provide next aid package for Greece (EUR 100 billion, with 15 years repayment period). The interests on the loan were lowered to 3.5% (with regard to previously agreed 5.5%). The private investors and government institutions voluntary agreed to the cut of the nominal value of the Greek bonds (21.07.2011).
During the next summit, in October 2011 the politicians made important decision to reduce the risk of crisis contagion from Greece to the other EU countries. Moreover, the EU countries agreed on a plan which would help to cut the debt of Greece from 160% to 120% of GDP up to 2020. In order to implement these actions, it was proposed that all owners of Greek governmental bonds would "voluntary" accept a 50% cut of their bonds and reduction of interest rates to 3.5%. In order to receive another loan, Greece would have to implement further austerity measures. On February 21, 2012 the second bailout package was finalized. Private investors accepted even slightly bigger cut of the face value of Greek bonds (53.5%). This deal was the biggest restructuring deal all over the world. The creditors were invited to swap their bonds into the new ones of maturity 11 to 30 years and lower average yield (3.65%). If not enough creditors agreed to swap their bonds, the Greek government would decide to introduce a collective action clause. Eventually, on March 12, 2012 the ISDA decided to trigger the credit event.

3 Credit event

These decisions of the EU summit in October 2011 were widely commented by the press and by the market analysts. Speculations arose whether the situation should trigger the credit event or not. The International Swaps and Derivatives Association, the industry body that decides whether CDS should pay out, decided that Greece's proposed debt exchange did not currently activate swaps linked to the country's debt (Dealbook, 1.03.2012). Let us analyse the definition of the credit event.
In case of the European CDS, there are possible three kinds of "credit events" (after Grady & Lee, 2012):

A "Failure to pay" credit event – applies to all types of standard CDS transactions and is triggered by a payment default in an amount of at least USD 1 million by the reference entity on certain debt obligations after the expiration of any grace period;

A "Restructuring" credit event – triggered after the occurrence of one of five specified events with respect to the reference entity's obligations in relation to an amount of USD 10 million or more. These events are:

reduction in interest payable,

reduction in principal or premium payable,

- a postponement or deferral of certain payment or accrual dated,
- a change in ranking or priority resulting in "Subordination",
- a change in the currency of a payment to any currency that does not qualify as "Permitted Currency".

This credit event is triggered only if it results from deterioration in the creditworthiness or financial condition of the reference entity;

A "Repudiation/Moratorium" credit event applies only to sovereign CDS. This event can be triggered only if the following two conditions are satisfied:

- The sovereign entity must either repudiate or declare a moratorium on payments under its Obligations in relation to at least an amount of USD 10 million,
- "Failure to Pay" or "Restructuring" must occur within a specified period of time (generally 60 days after the initial repudiation or moratorium declaration), regardless of the amount of the affected debt.

Grady and Lee (2012) explained the legal nuisances that allowed not to trigger the credit event in the case of Greece. The International Swaps and Derivatives Association (ISDA) argued that Greece had not actually stopped paying the interests on its bonds. Moreover, the debt exchange was voluntary. However, some market analysts warned that "If a sovereign, and those trying to rescue it, tiptoe around the periphery to avoid triggering the C.D.S., it may impair the effectiveness of the C.D.S. as a risk management tool," (Bruce Bennett, a partner at the law firm Covington & Burling, after: Dealbook, 01.03.2012). They argued that the ability of CDS to price the sovereign risk properly was put in question. This statement was exactly the motivation for our research. Based upon the individual properties of the CDS spreads and the relationships between the CDS and bond spreads we assess the degree to which the CDS contracts are able to value the sovereign risk, comparing to the bond valuation, whether this ability changed after the Greek crisis, and whether any improvement was observable after the credit event had been eventually triggered.

4 Data description

In theory, the CDS spread and bond yield should be closely related one to another. Let us denote by S_t the value of the CDS spread, by Y_t the yield of the bond of corresponding maturity and by R_t the yield of the riskless bond. Approximately, the following relationship should hold:

$$S_t = Y_t - R_t. \tag{1}$$

If S_t is greater than $Y_t - R_t$, an investor may buy a riskless bond, short a risky one and sell the credit default swap. In the opposite situation, the investor will find it profitable to buy a risky bond, buy the credit default swap and short a riskless bond (see e.g. Hull, Predescu & White, 2004).

The research presented in this paper is in a sense an extension of the papers (Courdet & Gex, 2010) and (Courdet and Gex, 2011). Based upon the results presented by the authors we are aware of the fact in the so-called "high-yield" countries CDS prices lead the bond spread, while in the low-yield ones the relation is opposite. We make this statement the starting point of our research.

We take into account the daily CDS data of 10 years maturity (provided by *Datastream*) as well as daily values of indexes of yields of 10-years bonds (provided by stooq.pl). We analyse the following three groups of European countries: the Mediterranean one (represented by Italy, Greece, Spain and Portugal), the Central-European G3 (Czech Republic, Hungary and Poland) and the Western-European ones (represented by Finland, France, Denmark and the Netherlands). The data cover the period from January 2008 to the end of August 2012 (in the case of Denmark from January 2009 to the end of August 2012). In all the cases we took into account the CDS contracted on Eurobonds, except for Finland and Netherlands where the dynamics of the USD CDS spreads was higher and the data more complete.

Following (Courdet & Gex, 2010) we assumed that we can approximate the yield of the riskless bond with the yield of the German bond. Thus, we constructed the bond spreads subtracting the yield of German bond (assumed to be the risk-free one) from the given bond yield. Figures 1 to 11 present the obtained series. It is clear that in general they follow the same pattern. However, in some cases the series move more closely one to another than in others. Obviously, the most diverse seem to be the Greek series.

Following (Coudret & Gex, 2010) we divide the countries into two subgroups: the low-yield (here: Finland, France, the Netherlands and Denmark) and the high-yield countries. In the group of the high-yield countries we distinguish also the already mentioned two subgroups: G3 countries (Czech Republic, Hungary and Poland) and the Mediterranean countries (Portugal, Spain, Italy and Greece).

Even by observing the evolution of the spreads we can spot some characteristic behaviour in each group. First of all – the CDS and bond spreads move very alike in the Mediterranean countries (Portugal, Spain, Italy) – the exception is Greece, where the diversity is clearly visible. Also in Hungary the relationship between the bond and CDS spreads seems to be obvious. In the case of Poland and Czech Republic we observe that the series change in similar fashion but they do not follow strictly each other.

In the case of the low-yield countries we can observe some interesting patterns. Let us first concentrate on the Danish bond spread. Up to May 2010 the CDS and bond spreads almost overlapped. Starting from May 2010 we can observe more and more discrepancies. Moreover, since November 2011 the bon spreads take values lower than zero. These diversities of the bond and CDS spreads coincide with the beginning of the problems of the Mediterranean countries. It seems that Germany, as the most stable and representative economy of the European Union, was also hit by the Greek crisis, while the smaller economies were more robust. In the case of the low-yield group (Finland, France, Denmark and the Netherlands) we can also observe that starting from January 2010 the gap between the CDS and bond spreads widens systematically, which may be considered as a suggestion that the valuation of risk via bond and CDS spreads changed.

In no case – except for Greece – we observe a reaction to triggering the credit event (12.03.2012). In the case of Greece we notice a sudden drop of the bond spread, while the level of the CDS spread remains constant (no transactions).

Figure 1: CDS spread (grey line) and Greek bond yield spread (black line)

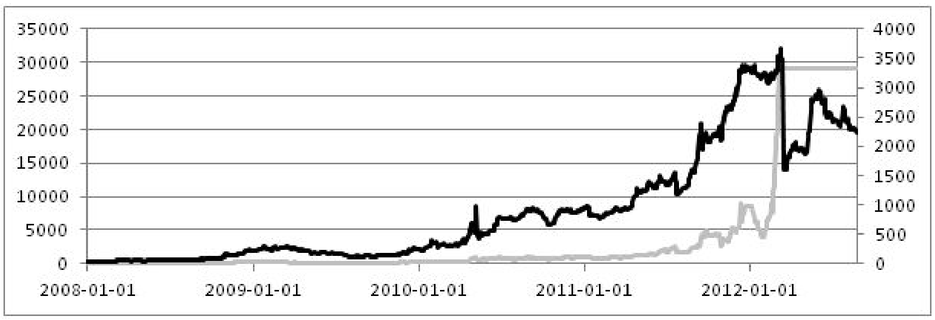
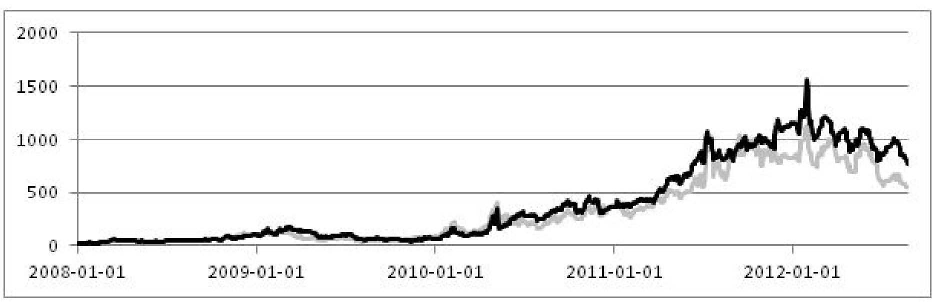


Figure 2: CDS spread (grey line) and Portuguese bond yield spread (black line)



Note: due to the lack of data on the contracts for Euro-bonds, we estimated the missing data using prices of the contracts for USD-bonds.

Figure 3: CDS spread (grey line) and Spanish bond yield spread (black line)

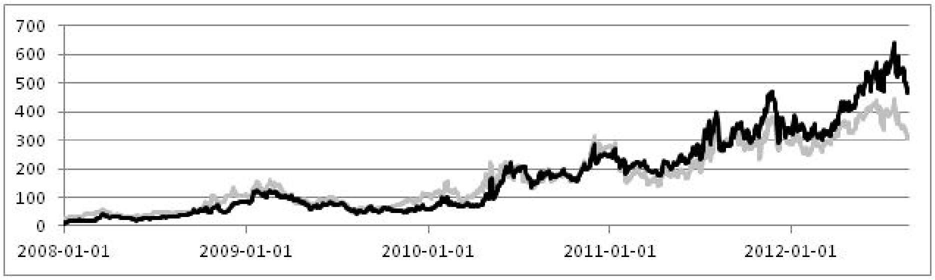


Figure 4: CDS spread (grey line) and Italian bond yield spread (black line)

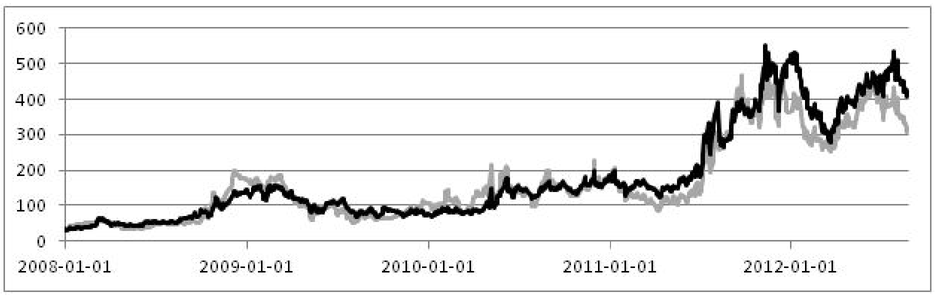


Figure 5: CDS spread (grey line) and Polish bond yield spread (black line)

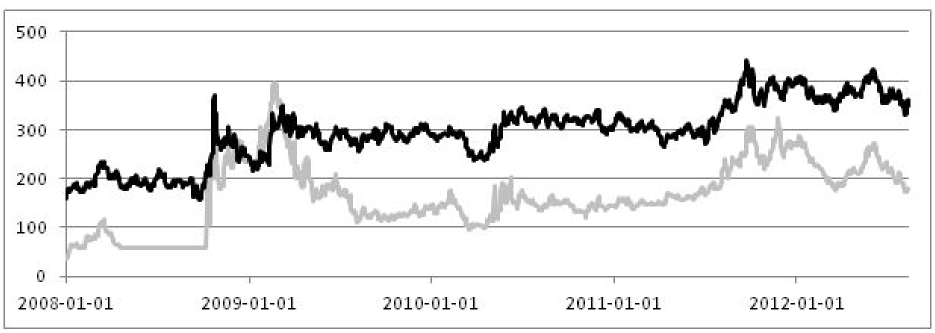


Figure 6: CDS spread (grey line) and Hungarian bond yield spread (black line)

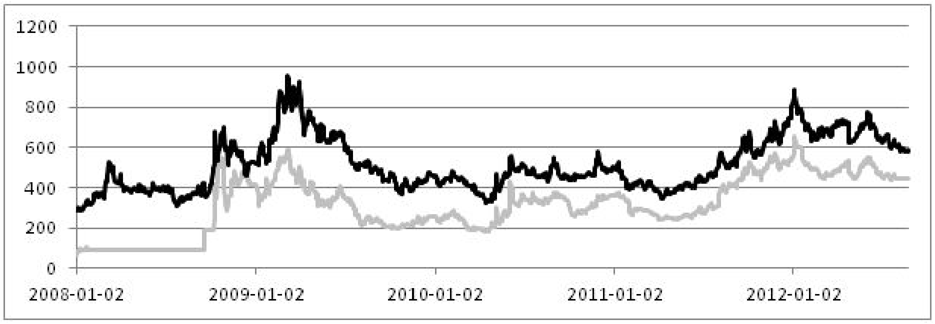


Figure 7: CDS spread (grey line) and Czech bond yield spread (black line)

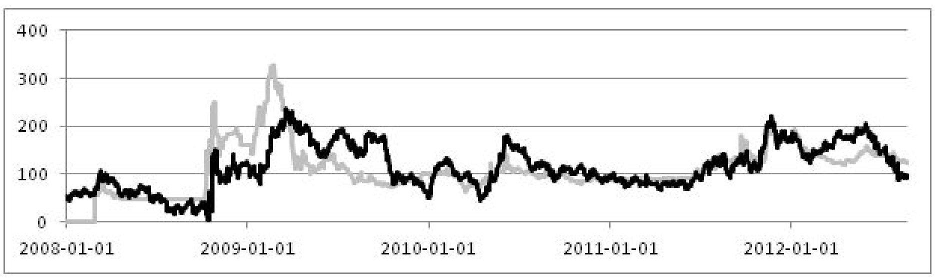
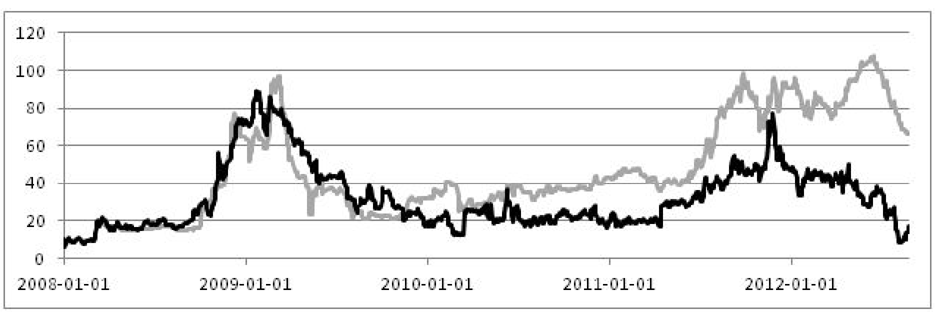


Figure 8: USD CDS spread (grey line) and Finnish bond yield spread (black line)



In Table 1 (see Appendix) we present the descriptive statistics of the first differences of the investigated data (we took into account the differences of the series in order to guarantee their stationarity). Let us note that in most of the cases the bond

Figure 9: CDS spread (grey line) and French bond yield spread (black line)

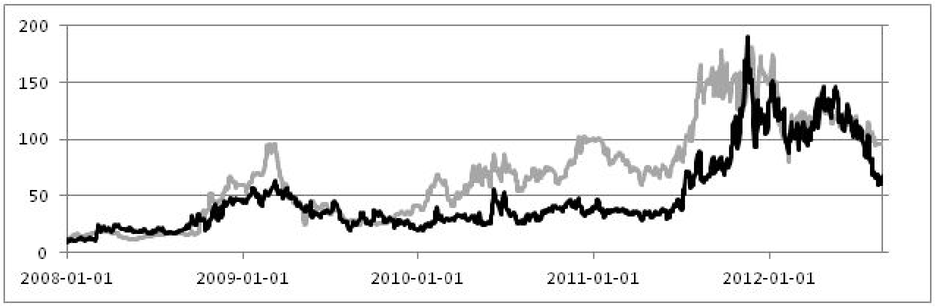


Figure 10: CDS spread (grey line) and Danish bond yield spread (black line)

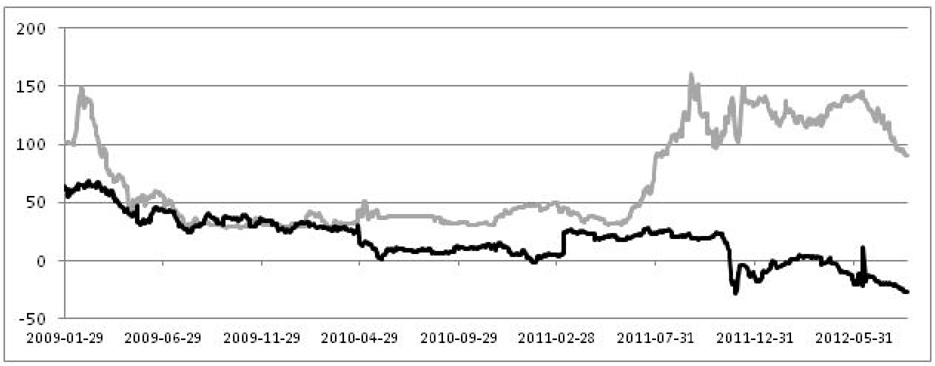
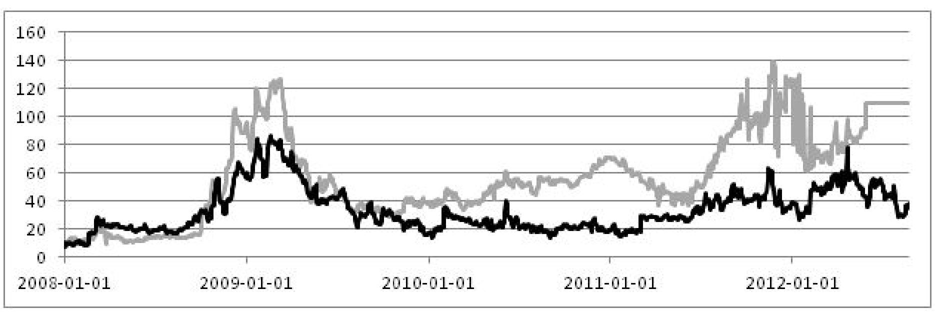


Figure 11: USD CDS spread (grey line) and Dutch bond yield spread (black line)



spreads changes were less volatile than the CDS spreads ones (when the volatility was measured by the standard deviation of the series) – the exception were Czech Republic and Hungary as well as Spain and Finland, where the differences were however not so sharp. We can also observe that the most volatile series were the ones of Greece, Portugal and Hungary, while the lowest values of standard deviations were observed in the case of the so called "low-yield" countries. Tables 2 and 3 present the values of the Box-Pierce test performed for the raw and squared data (changes of the spreads). Let us note that in the case of bond spread changes we observe autocorrelation of raw series in all cases, while there is no ARCH-effect in the Greek data. In the case of CDS spread changes – we find autocorrelation in raw and squared data of all series. Additionally, we performed the long-memory test of Geweke and Porter-Hudak (1983) (see the next paragraph for details). The results are presented in Table 4. We reject the hypothesis of long memory for Portuguese, Czech and Hungarian data, as well as for Polish CDS, Finnish, French and Dutch bonds. In most of the remaining cases the parameter d took small negative values. The highest positive value is observed for Greek bonds – 0.3.

5 Methodology

We estimated three kinds of models for each data pair: the AR(FI)MA-GARCH, the MS-AR(FI)MA and the MS-AR(FI)MA-GARCH. Our goal was to find the model best describing the data. We took into account the ability of the model to explain the linear and non-linear dependencies, to distinguish the regimes properly, as well as the information criteria, log-likelihood function value and the adjusted R-squared statistics.

5.1 Long memory

The statistics presented in Table 1 are relevant to the whole period over study. However, by looking at the Figures 1 to 11 we can observe hectic and tranquil times. The estimates of parameter d (Table 4) suggest that the long memory phenomena is present in the data and thus that it may be necessary to model the series via ARFIMA model, i.e. the so-called fractionally integrated model.

If the process under study is stationary: $I(0)$, the influence of the shock disappears after a limited number of periods (specified by the number of lags in ARMA process). If the process has a unit root (is $I(1)$), the effect of the shock lasts forever. There exists also a class of processes of the so called long memory, in which case the effect of the shock is persistent and disappears longer than in the case of the short-memory processes. Such a process is called a fractionally-integrated one and denoted by $FI(d)$. The ARFIMA model describing behavior of such a process has the following form:

$$\Phi(L)(1-L)^d(y_t-\mu_t)=\Theta(L)\varepsilon_t, \qquad t=1,\dots,T, \tag{2}$$

where y_t denotes the time series at time t, μ_y – its mean and $\Phi(L) = 1-\phi_1 L-\dots-\phi_p L^p$ is the stable autoregressive polynomial in the lag operator L, and $\Theta(L)=1+\theta_1 L+\dots+\theta_q L^q$ – the invertible moving average part

$(p, q \in \{0, 1, 2, \dots\})$. $\Phi(L)$ and $\Theta(L)$ together define the short memory characteristics of the model (see eg. Bos et al., 1999). The long memory is governed by the part $(1-L)^d$. If d is an integer, the $I(d)$ is non-fractional and taking d-th differences of y_t leads to I(0) process. If $d \in (0, 0.5)$, the process is said to exhibit long-memory property, and its partial correlations and autocorrelations decay monotonically and hyperbolically to zero, as the lag increases. If $d \in (-0.5, 0)$ we have the process of so called intermediate memory. If $d = 0$ the process is a white noise (see: Kwiatkowski, 1999).

However, as many researchers point out (see e.g. Diebold & Inoue, 2001, Choi et al., 2010, or Choi and Zivot, 2007), the long memory effect can be also caused by or confused with the structural break. Choi and Zivot (2007) show also that in some cases the long memory can however still be present in the data, even after adjusting for structural breaks. Thus, apart from the long memory testing, we decided also to verify the existence of possible breaks, estimating also a regime-switching model.

5.2 Regime switching

Allowing for regime-switching we assume that the process under study is driven by another unobservable one which can be interpreted e.g. as the state of the economy, identified by the regime. There are various types of regime-switching models. The simplest one is the Markov-Switching one, where the switching is under control of a Markov-chain updating mechanism with fixed transition probabilities (Hamilton, 1989). Let us denote by y_t the value of the process at time t, and by s_t the unobservable variable taking binary values and indicating the state of economy. Let us also denote the probability density of the dependent variable at time t during regime i by: $f(y_t|s_t = i, \Psi_{t-1})$, where Ψ_{t-1} denotes the σ-algebra containing the history of the process up to time $(t-1)$, while s_t – the current regime. Then, the probability of falling into the i-th regime at time t is given by (see eg. Davidson, 2013, Kim and Nelson, 1999):

$$P(s_t = i|\Psi_t) = \frac{f(y_t|s_t = i, \Psi_{t-1}) P(s_t = i|\Psi_{t-1})}{\sum_{k=1}^{M} f(y_t|s_t = k, \Psi_{t-1}) P(s_t = k|\Psi_{t-1})}, \tag{3}$$

where

$$P(s_t = i|\Psi_{t-1}) = \sum_{k=1}^{M} p_{ik} P(s_{t-1} = k|\Psi_{t-1}). \tag{4}$$

The probabilities of transition, denoted by $p_{ik} = P(s_t = i|s_{t-1} = k)$ are the parameters to be estimated. Obviously, $\sum_{k=1}^{M} p_{ik} = 1$. The model is estimated via maximizing the likelihood function of the following form:

$$L_t = \sum_{t=1}^{T} \ln \sum_{k=1}^{M} f(y_t|s_t = k, \Psi_{t-1}) P(s_t = k|\Psi_{t-1}). \tag{5}$$

In our study we model the first differences of data through Markov-Switching Dynamic Regression models with explanatory variables(z_t), and Markov-Switching ARMA-GARCH models (Bollerslev, 1996). We started from the most general approach, and allowed for switching all possible parameters (z_t) - i.e. ARMA coefficients, the coefficients at the explanatory variables, as well as GARCH parameters:

$$\begin{aligned} & y_t = \alpha(s_t) + \sum_{i=1}^{p} \beta_i(s_t) y_{t-i} + \sum_{j=1}^{q} \gamma_j(s_t) z_{t-j} + r_t, \\ & r_t = \sqrt{h_t}\varepsilon_t, \\ & \varepsilon_t \sim iid(0,1), \\ & h_t = \varpi(s_t) + \sum_{i=1}^{p} \alpha_i(s_t) r_{t-i}^2 + \sum_{j=1}^{q} \beta_j(s_t) h_{t-j} \end{aligned} \tag{6}$$

If there is no ARCH-effect in the data, the equation for h_t reduces to: $h_t = \varpi(s_t)$. The regime characterised by higher standard deviation or higher ω was associated with the crisis period. We estimated the model starting from the simplest one, and complicating it if needed. First, we estimated the AR(FI)MA-GARCH model with no switches, next the MS-AR(FI)MA model and as a last step, the MS-AR(FI)MA-GARCH one. We chose the best model based upon its ability to explain linear and non-linear dependencies of the series, its fit to the data (based upon the statistics used to assess goodness-of-fit of linear model, such as R^2 and corrected R^2), its ability to identify the regimes properly and the information criteria.

In order to estimate the Markov-Switching models we used OxMetrics6 (PC-Give package: `http://www.doornik.com/pcgive/`, Markov Switching Dynamic Regression model) and TSM4 software (`http://www.timeseriesmodelling.com/`).

5.3 Other GARCH-type models used to model volatilities

Apart from the basic GARCH(p,q) model we used also some other types of GARCH family. These were: EGARCH, PARCH and ARCH models. We present their equations below.

The ARCH (Engle, 1982) does not include the lagged value of h_t and thus it is assumed that the conditional variance is driven only by innovations:

$$h_t = \varpi + \sum_{i=1}^{p} \alpha_i r_{t-i}^2. \tag{7}$$

The PARCH (Ding, Granger and Engle, 1993) one is a more general one, encompassing among others also the GARCH(p,q) model:

$$h_t^{\frac{\delta}{2}} = \varpi + \sum_{i=1}^{p} \alpha_i r_{t-i}^{\delta} + \sum_{j=1}^{q} \beta_j h_{t-j}^{\frac{\delta}{2}}. \tag{8}$$

Eventually, the EGARCH (Nelson, 1991 and Bollerslev & Mikkelsen, 1996) model is given by:

$$\begin{gathered} \ln(h_t) = \omega + \sum_{i=1}^{p} \alpha_i g(\varepsilon_{t-i}) + \sum_{j=1}^{q} \beta_j \ln(h_{t-j}) \\ g(\varepsilon_t) = \gamma_1 \varepsilon_t + \gamma_2 (|\varepsilon_t| - E|\varepsilon_t|) \end{gathered} \quad . \tag{9}$$

The function $g(\cdot)$ takes into account the magnitude (γ_2) and sign of innovation (γ_1). The value of γ_2 is usually positive, meaning that the higher the deviation of the return from its expected value, the higher the volatility. Thus, the model includes the so-called leverage effect, described by Black (1976). Black observed that in the case of high drops we face higher volatility values than in the case of high increases. However, as in the case of CDS premia it is the decline, that is associated with a good piece of news, we would expect the opposite leverage effect. If $\gamma_2 = 0$ we assume that no leverage effect is present in the data.

6 Test for change of nature of the relationship – the Markov Switching model

Let us once again remind the starting point of our research: based upon the papers of Coudret and Gex (2010 and 2011) we could assume that in high-yield countries the bond market leads the CDS one, while in the low-yield ones the relationship is opposite. Thus, in order to verify the possible changes in relationships of the spreads before and during the Greek crisis, we decided to model changes in adequate spreads via AR(FI)MA-type Markov-switching models, where the explanatory variables were the lagged changes of CDS and lagged changes of bond spreads. In this way we were able to verify whether the Greek crisis was identified by the regime of higher variance and distinguishable from the turmoil of 2008/2009, as well as to check whether the relationship between the instruments changed together with the change of regime. Analysis of conditional variance helped us to assess the results. For instance, if the coefficient on the explanatory variable became insignificant in the regime identifying the Greek crisis, this would suggest the deterioration of the relationships. The results are presented in Tables 5 to 18 in Appendix, while the obtained regimes are pictured in Figures 12 to 15 Let us shortly discuss the obtained results.

6.1 Mediterranean group

We were able to identify the lead relationship of CDS only in case of two countries. This was Portugal and Greece. In case of all the countries we identified the high and low-variance regimes. If the high variance regime overlaps with the Greek crisis (Greece, Spain and in a way - Portugal), we interpret the coefficients of this regime as the coefficients during Greek crisis.
Thus, in the case of Portugal we can observe the change of regime already at the

beginning of 2009 (Figure 12c). Next, the process returns to its low-volatility regime and stays there until 2010 (together with the beginning of Greek problems). The series return to the low-variance regime in 2011 but only for short. Change of the bond spread depends on the change of CDS spread from the previous period in both regimes, however in the case of the mean equation, the sign of the coefficient does change and thus, we can conclude that the risk is valued differently by bond and CDS spreads in both regimes (Table 4). However, we found also dependencies between the variables in variance. The relationships do not change during the crisis and hence the variability of the risk did not change together with the outbreak of the Greek crisis. The estimated model was the ARMA-ARCH model (see Table 7).

In the case of Greece the best model was the MS-ARMA. Since after fitting the MS-ARMA model we identified no dependencies in the squared returns neither through Box-Pierce nor the ARCH test (see Table 2), we assumed this one to be the best one. Based upon the chosen model we observe that the relationships were broken during the Greek crisis – the coefficient on the lagged value of CDS spread change became insignificant. Thus, the valuation of risk became different. It is also worth noting that during the crisis the turnover of the Greek CDS was close to null and the quoted prices were only the offered ones (Table 1). Let us point out the extreme return in March 2012, in the day of triggering the credit event, which was not seen in any other of the analysed series.

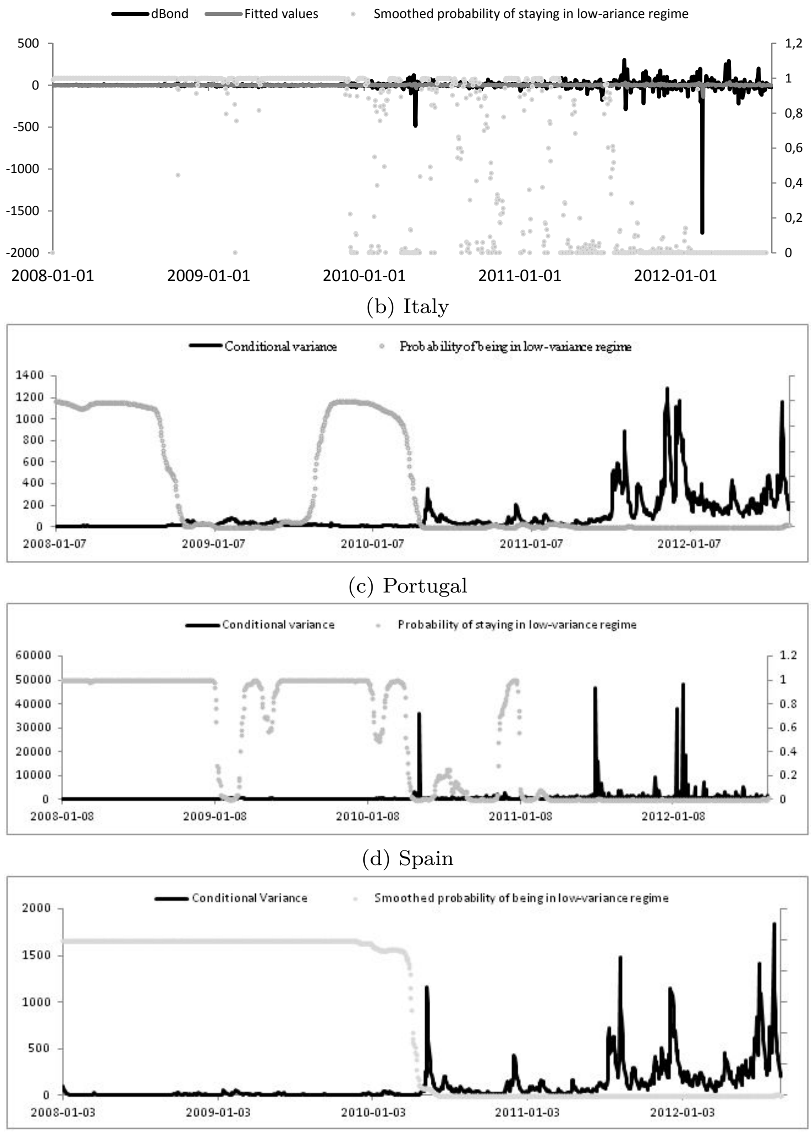
In the case of Italy and Spain the lead relationship of CDS was not proven. We found no dependence of bond spreads changes on the lagged values of the CDS spread changes (Table 2 and 4). However, in the case of Spain the high-variance regime overlaps with the Greek crisis (see Figure 3 and 12b). In the case of Italy the high-volatility regime overlaps not only with the Greek crisis period, but also with the beginning of the financial crisis. In both cases we modeled volatility through the Exponential GARCH model, however assuming no asymmetry.

Volatilities of the four series behaved especially hectic during the Greek crisis period (see Figure 12). Even in the case of Italy, where the high-variance regime covers the beginning of the Financial crisis and the Greek crisis, the volatility dynamics in both phases is incomparable. In the case of all of the series the first pick is present on May, 11th, 2010. Next period of volatility picks starts in Summer 2011, and in the case of Spain and Italy covers also the second half of 2011, as well as beginning of 2012. In the case of Portugal, we observe extremely high picks in June 2012.

Since in the case of Spain and Italy we did not find any significant proof that the CDS market leads the bond one for the instruments of 10-years maturity, we checked also for the opposite relationships. The results of the estimations are presented in Tables 9 to 13 and in the Figure 13. Once again, we can observe that the high-variance regime overlaps with the Greek crisis. However, in the case of Italy and Spain they cover also the hectic beginning-of-crisis period.

The most interesting results were obtained for Greece. In order to explain all the linear dependencies in the data we needed to use 3-regime model – see Table 9.

Figure 12: Identified regimes and volatility of scaled residuals – Mediterranean group (respectively: Greece, Italy, Portugal, Spain) – models for the bond spreads



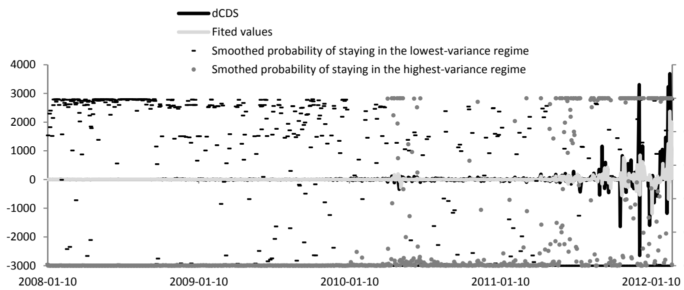
(a) Greece
(b) Italy
(c) Portugal
(d) Spain

Pure ARMA-GARCH model was not able to explain the whole data dynamics, while adding the GARCH component to the MS-ARMA model resulted in even worse fit.

The regime of the highest variance is denoted as the regime 2. In this regime, which clearly overlaps with the Greek crisis period (see Figure 13a), the current value of the CDS return depends only on its 4-days lagged value. All the relationships with bond spreads are broken. On contrary, in the lowest-variance regime, denoted as regime 1, we observe dependencies on the lagged values of bond spread (up to the lag 6) and of the CDS spread (up to the lag 5). The same is true for the moderate-variance regime. The model was estimated for the shorter subsample, ending on March 1, 2012, due to the lack of transactions on CDS in later period (see also Figure 1). The model leaves unexplained ARCH effect, however, as already stated, adding the GARCH part to it worsened its fit to the data and did not allow for proper identification of regimes.
In the case of the other CDS spreads we needed only 2 regimes to explain all the linear dependencies. And thus, the Italian CDS spread proved to be dependent on the lagged values of the bond spread, but only in the high-variance regime and with p-value 0.056. The relationships ceased in the tranquil periods. However, the high-volatility regime was identified not only during the Greek problems, but it covered much wider period (see Figure 13). The fitted model did not explain the non-linear dependencies in the data, however was preferred by the information criteria and overall model fit (corrected R^2).
In the case of Spain the best model included the GARCH part, however it did not allow to distinguish the regimes properly (see Table 10 and Figure 13d). The absorbing regime was the low-variance one. However, it appears that the bond market led the sCDS one in the high volatility regime. The period of staying in the regime was very short and usually after a day or two the relationships changed. For instance, on May, 10, 2010 the process stayed in the high-volatility regime (with probability 0.9), next day the volatility reached its pick and the relationship was broken. The model outperformed the ARMA-GARCH model excluding the switch. However, since the time of remaining in the regime was so short, we can conclude that on average there was no lead relationship of the bond market over the sCDS one.
Eventually, in the case of Portuguese CDS spread, we identified two regimes, from which the low-variance one was the absorbing regime. However, as the coefficients representing the relationships between the two series are significant in both regimes, we conclude that the dependencies were present no matter of the Greek situation. The long memory coefficient was present in the low-variance regime and took a small value of 0.8, while in the high-variance regime the long memory effect disappeared (see Table 11).
It is worth noting that in the case of Portugal and Spain the picks in volatility appeared in the same moments, i.e. in May and December 2010, in the second half of 2011 and the beginning of 2012. We observe no clear reaction of volatility to triggering the credit event, volatilities of both series were low in March 2012.
Concluding, in the case of the Mediterranean countries as a group we found no clear lead-lag relationship between the CDS and bond market. Thus, we can suppose that the causality relationship is bilateral (feedback) in the case of Greece and Portugal,

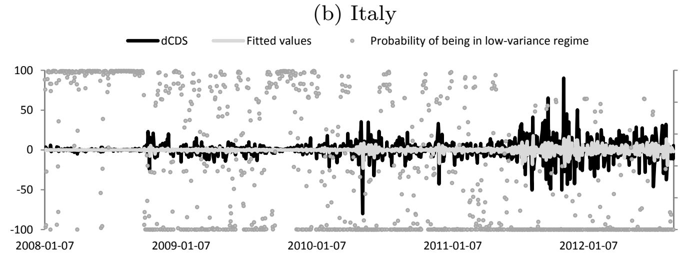
Figure 13: Identified regimes and volatility of scaled residuals – Mediterranean group (Greece, Italy, Portugal, Spain) – models for the CDS spreads

(a) Greece

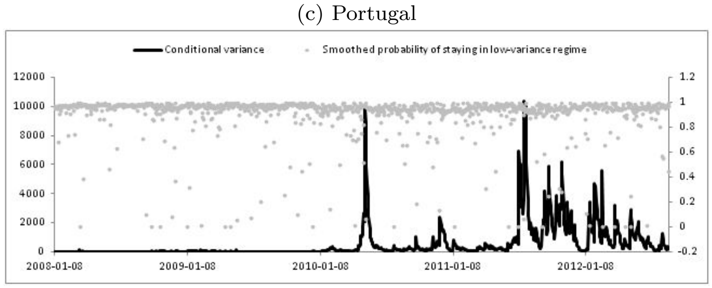


Note: the series in the picture end in March 2012.

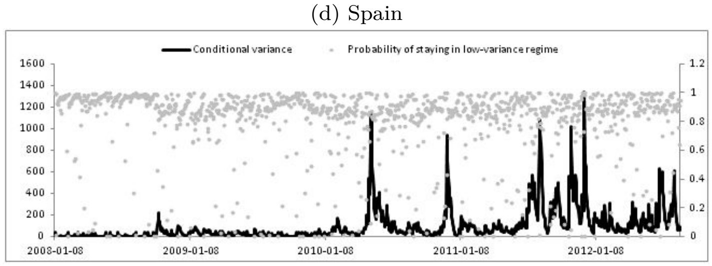
(b) Italy



(c) Portugal



(d) Spain



and that the bond market leads the CDS one in the case of Italy (weak evidence).

The feedback between the CDS and Portuguese bond spreads was reported also by O'Kane (2012) – however, in the case of Greece the author reports causality from CDS to bond market. Only in the case of Greece we proved that the relationship between the two risk measures was broken and the CDS became rather useless instruments of risk pricing. Also only in the case of the Greek bond spread did we observe a significant reaction of variance to triggering the credit event. However, volatilities of all instruments seemed to react to subsequent events during the Greek crisis. Moreover, the reaction to Greek crisis is seen in volatility and based upon the obtained results we can conclude that there was no contagion from CDS market to the bond one (nor the other way round), but a common reaction to the shocks.

6.2 The Central-European group

In the case of the G3 group we can observe quite different patterns. First of all, the Greek crisis is undistinguishable from the turmoil of 2009 (see Figure 14), which was not the case in the Mediterranean group (we introduced also the third regime in order to verify whether this would allow for identification of the Greek crisis, but with no effect).

The regimes were clearly identified in the case of Poland and Hungary. In the case of Czech Republic we estimated the MS-ARMA-GARCH model, but the low-variance regime was again the absorbing one. However, since this model outperformed the ARMA-GARCH, as well as MS-ARMA, we chose the one.

In the case of Czech Republic the dependence of the bond spread on the CDS spread is observable only in the high-volatility regime (see Table 14). However, contrary to the South-European case, the period of 2008/2009 is much more volatile than the Greek crisis one (Figure 14a). Thus, we cannot state that there was a change in the dependencies between the bond and CDS market due to the Greek problems. We did not find any reaction to triggering the credit event either.

In the case of Hungary the regimes were properly identified. The lead-relationship of the CDS market was present in both regimes. Volatility was modeled via ARCH model. Although the ARCH coefficient was insignificant, the model was better that the one without the ARCH effect. The regimes did not overlap only with the Greek crisis, but also with the hectic period of 2008/2009 and with the period of Hungarian problems (Figure 14b). Again, no reaction to triggering the credit event was found.

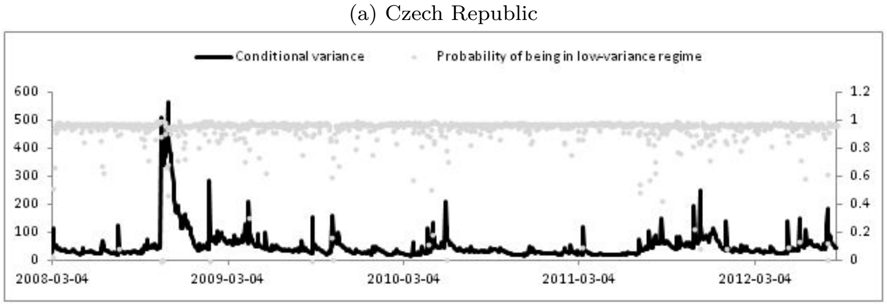
Eventually, in the case of Poland, the regimes were clearly identified (Figure 14c). Two periods of high volatility were found: the 2008/2009 period and the one starting in July 2011. The first one can be associated with the transmission of the crisis to the Central Europe and the speculative attacks for the local currencies, the second one - with the Greek problems. However, we have also evidence to suppose that this high-variance regime identified in the middle of 2011 was also influenced by the problems in Hungary, not solely by the Greek crisis (see also: Kliber, 2011). If we observe the patterns of volatilities of Czech and Polish series, we note that the dynamics was much higher in the first phase of the crisis, than during the Greek problems. From June

2010 to July 2011 the series remained in the low-variance regime and the changes of volatilities were not so hectic. At the same time we observe the rapid changes of regimes in Hungary, which is the clear picture of the problems of the country's economy.

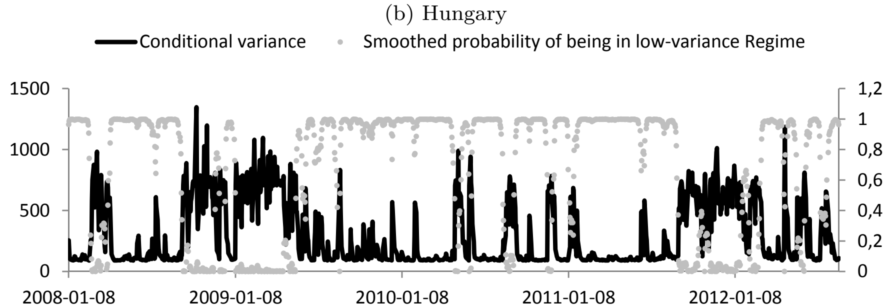
In the case of Polish data we did not prove the existence of the lead relationship of the CDS market. Also the reaction to triggering the credit event was not found.

Figure 14: Identified regimes and volatility of scaled residuals – Central-European group (Czech Republic, Hungary, Poland)

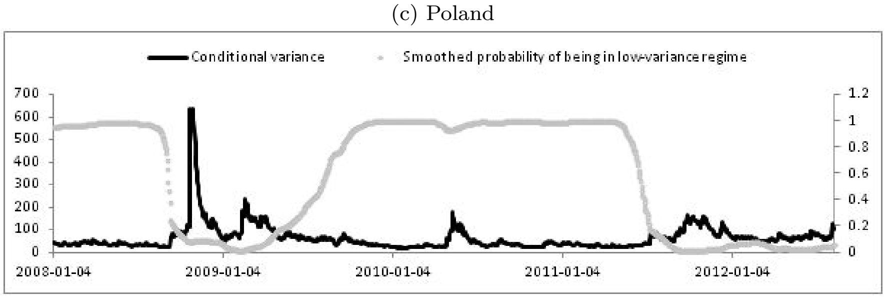
(a) Czech Republic



(b) Hungary



(c) Poland

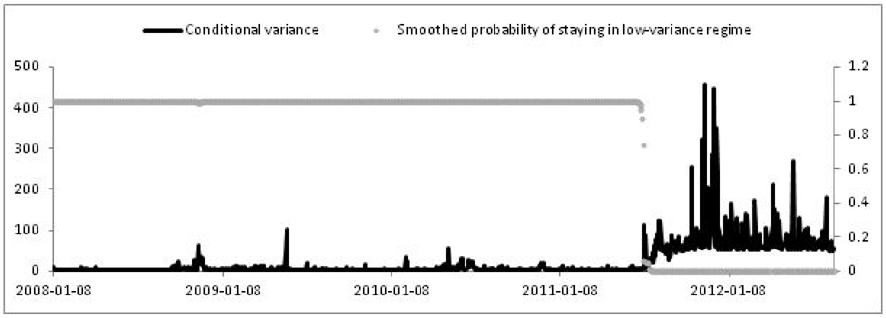


6.3 Low-yield countries

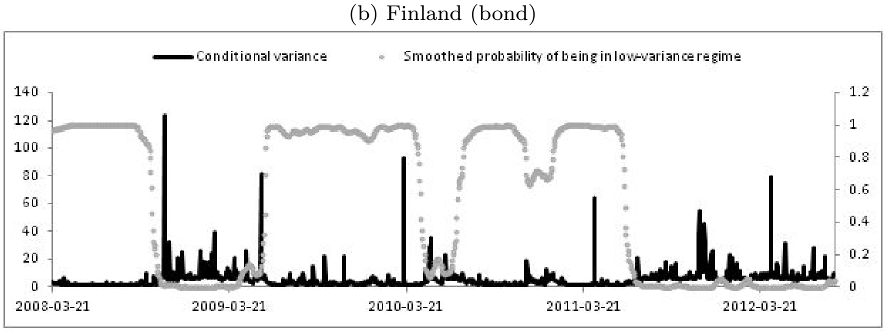
Eventually, in the third group of low-yield countries, we modeled the changes in CDS prices and verified whether or not they depended on the changes of the bond spreads. Since in the case of France and Finland we did not find the CDS-lead relationship between the bonds and CDS spreads, we modeled the bonds (see Figure 14a, 14b).
In the case of France we introduced the explanatory variables both into conditional mean and variance equations. The regimes were well-identified and the high-variance one overlapped clearly with the Greek-crisis period. What is interesting, in high-variance regime the lead-relationship of sCDS market was observed in mean, while in the low-variance regime such a relationship was observed in variance. We can conclude that together with the Greek crisis the relationships between the markets did change. In Figure 15 a) we observe the change of the volatility pattern. The series entered the high-variance regime in July 2011. Thus, the Greek crisis seemed to influence the interrelationships between the two markets.
In the case of Denmark neither the Greek crisis was identified as a different regime, nor was any lead-lag relationship between the risk measures found. Thus, we do not present the results here. However, based upon the Figure 10 we can say that risk valuation via bond and CDS spreads was different before and during the crisis. This result may be the consequence of the fact, that the bond spread became negative starting from the beginning of the Greek crisis. The results may have been different if other risk-free rate was chosen.
In the case of Finland, we run two models, testing for the lead-lag relationships, and similarly to the French case, we found the CDS market led the bond one. The regimes were identified properly, yet the high-volatility regime covered two periods: the 2008/2009 phase as well as the Greek crisis (Figure 15b) . In the high-variance regime the leading relationship of the sCDS market got broken. Yet, this is not the consequence of the Greek crisis, but the situation repeats every time, the market is more nervous (Table 17).
In the case of the Netherlands, adding the GARCH part to the ARMA-MS model did not improve the fit of the model, and thus we present the one without the conditional variance part. Based upon the Figure 15c) and the results presented in Table 18 we observe that the high-variance regime covers two periods: the beginning of crisis and the Greek turmoil. The relationship between the risk measures was found in both regimes. Adding the third regime did not allow us to identify the Greek crisis as a separate regime. However, we observe a significant growth of volatility values and dynamics at the end of 2011 and beginning of 2012, which can suggest that the Greek problems affected the Dutch CDS market in some way.

Figure 15: Identified regimes and volatility or fitted values – low-yield group (France, Finland and Netherlands)

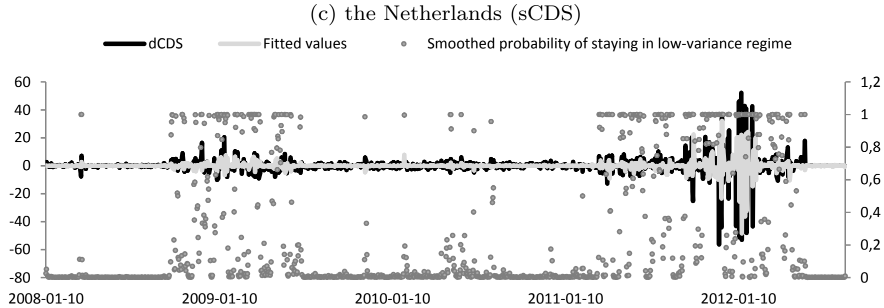
(a) France (bond)



(b) Finland (bond)



(c) the Netherlands (sCDS)



7 Conclusions

We can associate the high-variance regime with Greek crisis only in the case of four models: Spanish sCDS, Greek sCDS, Greek bonds and French bonds. From this four models in the case of both Greek models and the French one the relationships between the markets were broken during the Greek crisis. Summarizing the results presented in this paper, we can conclude that the Greek crisis did not cause deterioration of the whole European CDS market. First of all, in lots of the analysed cases, the Greek crisis is not distinguishable from the early-crisis turmoil (e.g. the whole Central Europe, Finland, the Netherlands). Only in the case of the Mediterranean countries and France the Greek crisis is clearly identified and distinguishable from the 2008/2009 turmoil both by regimes and volatility behaviour. We also observe growing gap between the Danish spreads, but we believe that this is due to the assumption of German bonds' yield as the risk-free one and reflects rather the growing risk aversion in Germany than in Denmark.

At the end of 2011 and beginning of 2012 we observe growth of volatility values and dynamics of the French and Dutch series (the latter measured by the absolute value of the price change), as well as of all South-European ones. Volatilities of Portuguese, Italian and Spanish series grew also in spring and summer 2010, probably as a reaction to the first phase of the Greek crisis. Quite exceptional is the situation of Finland, where volatility of bond spread did not react to the Greek crisis more than to the crisis transmission in 2008/2009. The same was true in the case of the G3 group. The pan-European growth of volatility at the end of 2011 and beginning of 2012 is noticeable also in the dynamics of the series, yet the reaction is not comparable to the hectic dynamics at the beginning of the crisis. However, the growth of volatilities of the series in 2011/2012 may suggest that triggering the credit event was a right decision. Even if the long period in which the credit event had not been triggered did not convince the investors to leave the CDS market, the growing nervousness contributed to the growth of the volatility of the instruments.

The results seem quite optimistic; however, we must point out some facts. First of all, the results presented in the paper apply to the instruments of long maturity (10 years). The CDS instruments of such maturity are not so popular and so intensively traded as the 5-years one. Besides, the investors trading for short term (e.g. one year) may behave differently to the long-term investors. In order to complete the picture, a similar study should be run using instruments of shorter maturity.

To summarize, if we take into account the market for instruments of long maturity, we can suppose that not triggering the credit event during the Greek crisis did not convince the investors to leave the CDS market. The only market affected in this way was the Greek CDS one (and indeed, there was no transaction on the Greek CDS since the crisis outbreak, and for a long time the quoted prices were only the offered ones) and the French one. However, the situation of France seems to be much different (compare Figures 1 and 9). There must have been the growth of volatility of French bonds and sCDS. While in the tranquil period the growth of sCDS volatility caused a subsequent growth of the bond spread one, not affecting the mean, in the hectic one the changes of the mean values seems to be opposite, namely the increase of the sCDS spread was followed by the decrease on the bond one. It seems that the Greek crisis affected the strong European economies much more than the weaker ones. There appeared a change of relationships but they were not totally broken. The CDS market for bonds of other European countries, including the Mediterranean ones, seems to function properly and the valuation of risk by CDS prices seems to be adequate – comparing with the risk pricing by the bond spreads.

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A Appendix

A.1 Descriptive statistics of the data

Table 1: Descriptive statistics of the first differences of the CDS and bond spreads

Country - instrument	Minimum	Mean	Maximum	Std.dev
Greece – CDS	-2645.00	24.11	5122.50	295.83
Greece – bonds	-1761.20	1.83	301.80	63.89
Italy – CDS	-79.98	0.24	90.13	10.52
Italy – bonds	-79.40	0.32	56.90	10.06
Portugal – CDS	-192.48	0.43	175.57	21.94
Portugal – bonds	-179.20	0.63	223.80	19.58
Spain – CDS	-66.52	0.24	63.35	10.07
Spain – bonds	-80.00	0.39	57.40	10.24
Czech – CDS	-50.00	0.06	55.00	6.48
Czech – Bonds	-46.80	0.04	62.70	7.65
Hingary – CDS	-85.00	0.32	128.89	13.85
Hungary –bonds	-103.80	0.26	115.10	18.14
Poland – CDS	-83.51	0.12	82.22	8.73
Poland – bonds	-45.30	0.17	82.50	8.10
Denmark – CDS	-179.20	-0.01	18.72	2.95
Denmark - bonds	-179.20	-0.10	32.70	2.33
Finland – CDS	-10.00	0.04	10.00	1.82
Finland – bonds	-11.10	0.01	14.60	1.89
France – CDS	-29.62	0.07	26.35	4.21
France –bonds	-24.30	0.05	25.80	4.03
Netherl. – CDS	-56.35	0.08	52.18	6.07
Netherl. – bonds	-15.10	0.02	17.50	2.32

A.2 Models parameters

Notes:

$dCDS_{t-i}$ denotes the lagged value of the CDS spread change by i periods;

$dBond_{t-i}$ denotes the lagged value of the bond spread change by i periods;

Other parameters correspond to the ones in equations: (5), (6), (7), (8);

Italics denote the insignificant values;

A.2.1 Mediterranean group

1. Coefficients of Markov-switching models for the CDS-lead relationship (Mediterranean group)

Table 2: Box-Pierce statistics for raw and squared data – changes of bond spread

		Raw data		Squared data	
		Q-statistics	p-value	Q-statistics	p-value
Italy	Q(5)	39.197	0.000	312.314	0.000
	Q(10)	42.779	0.000	418.361	0.000
	Q(20)	64.394	0.000	770.463	0.000
	Q(50)	162.429	0.000	1117.970	0.000
Greece	Q(5)	25.239	0.000	**0.345**	**0.997**
	Q(10)	38.298	0.000	**0.488**	**1.000**
	Q(20)	46.383	0.001	**0.503**	**1.000**
	Q(50)	78.346	0.006	**1.955**	**1.000**
Portugal	Q(5)	401.504	0.000	350.729	0.000
	Q(10)	590.656	0.000	460.691	0.000
	Q(20)	620.996	0.000	467.228	0.000
	Q(50)	770.530	0.000	494.588	0.000
Spain	Q(5)	70.466	0.000	208.635	0.000
	Q(10)	72.826	0.000	304.350	0.000
	Q(20)	85.216	0.000	545.797	0.000
	Q(50)	173.101	0.000	799.457	0.000
Czech Rep.	Q(5)	22.756	0.000	513.975	0.000
	Q(10)	31.857	0.000	729.488	0.000
	Q(20)	47.020	0.001	745.992	0.000
	Q(50)	79.454	0.001	791.058	0.000
Hungary	Q(5)	48.234	0.000	160.816	0.000
	Q(10)	56.680	0.000	220.062	0.000
	Q(20)	65.029	0.000	455.516	0.000
	Q(50)	166.222	0.000	548.325	0.000
Poland	Q(5)	24.826	0.000	182.778	0.000
	Q(10)	32.271	0.000	193.308	0.000
	Q(20)	41.430	0.000	209.963	0.000
	Q(50)	80.942	0.000	253.342	0.000
Denmark	Q(5)	60.647	0.000	187.111	0.000
	Q(10)	70.580	0.000	188.743	0.000
	Q(20)	81.511	0.000	189.080	0.000
	Q(50)	94.958	0.000	190.418	0.000
Finland	Q(5)	11.313	0.046	41.760	0.000
	Q(10)	**17.596**	**0.062**	71.215	0.000
	Q(20)	**28.647**	**0.095**	87.429	0.000
	Q(50)	**46.640**	**0.609**	104.321	0.000
France	Q(5)	21.383	0.001	999.423	0.000
	Q(10)	30.623	0.001	1471.330	0.000
	Q(20)	96.870	0.000	2638.070	0.000
	Q(50)	187.501	0.000	3570.460	0.000
Netherlands	Q(5)	**7.586**	**0.181**	52.466	0.000
	Q(10)	**18.185**	**0.052**	81.085	0.000
	Q(20)	32.589	0.037	89.001	0.000
	Q(50)	73.206	0.018	118.403	0.000

2. Coefficients of Markov-switching models for the bond-lead relationship relationship (Mediterranean group)

3. G3 group

4. Low-yield group

Table 3: Box-Pierce statistics for raw and squared data – changes of bond spread

		Raw data		Squared data	
		Q-statistics	p-value	Q-statistics	p-value
Italy	Q(5)	105.683	0.000	146.881	0.000
	Q(10)	109.928	0.000	246.601	0.000
	Q(20)	117.116	0.000	335.727	0.000
	Q(50)	212.272	0.000	804.382	0.000
Greece	Q(5)	401.504	0.000	350.729	0.000
	Q(10)	590.656	0.000	460.691	0.000
	Q(20)	620.996	0.000	467.228	0.000
	Q(50)	770.530	0.000	494.588	0.000
Portugal	Q(5)	62.200	0.000	104.728	0.000
	Q(10)	70.670	0.000	156.415	0.000
	Q(20)	132.331	0.000	325.171	0.000
	Q(50)	177.152	0.000	478.862	0.000
Spain	Q(5)	106.113	0.000	189.544	0.000
	Q(10)	115.827	0.000	283.188	0.000
	Q(20)	132.704	0.000	391.833	0.000
	Q(50)	197.540	0.000	653.112	0.000
Czech Rep.	Q(5)	23.239	0.000	559.889	0.000
	Q(10)	44.947	0.000	855.460	0.000
	Q(20)	68.890	0.000	948.297	0.000
	Q(50)	101.199	0.000	996.869	0.000
Hungary	Q(5)	47.918	0.000	229.435	0.000
	Q(10)	58.319	0.000	297.307	0.000
	Q(20)	98.546	0.000	527.281	0.000
	Q(50)	147.870	0.000	571.291	0.000
Poland	Q(5)	28.519	0.000	349.852	0.000
	Q(10)	45.834	0.000	447.713	0.000
	Q(20)	64.406	0.000	522.896	0.000
	Q(50)	106.556	0.000	555.695	0.000
Denmark	Q(5)	91.958	0.000	133.475	0.000
	Q(10)	99.565	0.000	288.701	0.000
	Q(20)	112.548	0.000	419.391	0.000
	Q(50)	165.649	0.000	830.273	0.000
Finland	Q(5)	39.683	0.000	204.333	0.000
	Q(10)	45.839	0.000	270.606	0.000
	Q(20)	57.602	0.000	340.924	0.000
	Q(50)	112.375	0.000	545.158	0.000
France	Q(5)	61.443	0.000	352.352	0.000
	Q(10)	74.422	0.000	629.885	0.000
	Q(20)	113.786	0.000	1012.290	0.000
	Q(50)	221.752	0.000	2144.020	0.000
Netherlands	Q(5)	364.542	0.000	624.340	0.000
	Q(10)	456.449	0.000	1006.510	0.000
	Q(20)	582.800	0.000	1307.090	0.000
	Q(50)	951.198	0.000	1808.100	0.000

Table 4: Long memory tests

Country	Bond change		CDS change	
	d parameter	p value	d parameter	p value
Greece	0.091	0.001	0.306	0.000
Italy	-0.104	0.000	-0.064	0.020
Portugal	**0.053**	**0.054**	**-0.031**	**0.261**
Spain	-0.093	0.001	-0.116	0.000
Czech Rep.	**-0.009**	**0.749**	**0.017**	**0.544**
Hungary	**-0.036**	**0.203**	**0.040**	**0.151**
Poland	-0.110	0.000	**0.019**	**0.499**
Denmark	-0.140	0.000	0.174	0.000
Finland	**-0.024**	**0.402**	0.145	0.000
France	**-0.022**	**0.418**	-0.114	0.000
Netherlands	**-0.060**	**0.029**	-0.230	0.000

Note: No long memory found for Portuguese, Czech and Hungary instruments, as well as for Polish CDS and Finnish, French and Dutch bonds (bolded values).

Table 5: MS-ARMA model coefficients - Greek Bond spread

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	0.8736	0.3213	2.7200	0.0070
Constant(1)	3.3324	6.7490	0.4940	0.6220
$dCDS_{t-1}(0)$	-0.0143	0.0036	-3.9900	0.0000
$dCDS_{t-1}(1)$	0.0041	0.0125	0.3280	0.7430
$dBond_{t-1}(0)$	0.2118	0.0493	4.3000	0.0000
$dBond_{t-1}(1)$	0.0682	0.0555	1.2300	0.2190
$\omega(0)$	8.2563	0.4070	20.3000	0.0000
$\omega(1)$	120.9970	5.5550	21.8000	0.0000
$P(0\|0)$	0.0489	0.0104	4.7000	0.0000
$P(0\|1)$	0.8710	0.0290	30.0000	0.0000

Note: In the high-variance regime we observe no dependence on the lagged values of CDS which was present in the low-variance one.

Table 6: MS-ARMA-EGARCH(1,1) coefficients – Italian Bond spread

	Coefficient	Std.Error	t-value	t-prob
$dBond_{t-1}(0)$	0.181	0.048	3.768	0.000
$dBond_{t-1}(1)$	0.157	0.065	2.421	0.016
$dBond_{t-2}(0)$	-0.119	0.036	-3.289	0.001
$dBond_{t-2}(1)$	-0.137	0.054	-2.535	0.011
$dCDS_{t-1}(0)$	0.023	0.043	0.534	0.593
$dCDS_{t-1}(1)$	0.137	0.093	1.469	0.142
$\ln(\omega)(0)$	6.741	5.319	–	–
$\ln(\omega)(1)$	0.338	0.494	–	–
Student's t d.f.$^{(1/2)}(0)$	2.512	0.338	–	–
Student's t d.f.$^{(1/2)}(1)$	1.839	0.264	–	–
EGARCH(0) α_1	0.333	0.082	4.067	0.000
EGARCH(1) α_1	0.087	0.084	1.037	0.300
EGARCH(0) β_1	0.977	0.014	69.223	0.000
EGARCH(1) β_1	0.964	0.027	35.388	0.000
$P(0\|0)$	0.998			
$P(0\|1)$	0.005			

Explanatory variable $dCDS_{t-i}$ was insignificant in both regimes, as well as the ARCH parameter in the second regime. The γ_1 was assumed to be equal to 0.

Table 7: MS-ARMA- ARCH(1) model coefficients – Portuguese bond spread

	Coefficient	Std.Error	t-value	t-prob
$dCDS_{t-1}(0)$	0.1238	0.0507	2.441	0.015
$dCDS_{t-1}(1)$	0.05077	0.0300	1.695	0.09
$dCDS_{t-2}(0)$	0.0698	0.0674	1.036	0.301
$dCDS_{t-2}(1)$	-0.0711	0.0311	-2.286	0.022
$dCDS_{t-3}(0)$	0.0430	0.0529	0.813	0.416
$dCDS_{t-3}(1)$	-0.0327	0.0240	-1.364	0.173
$dBond_{t-1}(0)$	0.1470	0.0559	2.63	0.009
$dBond_{t-1}(1)$	0.2743	0.0597	4.596	0
$dBond_{t-2}(0)$	-0.0575	0.0592	-0.971	0.332
$dBond_{t-2}(1)$	0.0596	0.0557	1.069	0.285
$dBond_{t-3}(0)$	-0.0396	0.0572	-0.692	0.489
$dBond_{t-3}(1)$	-0.0223	0.0532	-0.42	0.675
$\omega(0)$	2.6482	0.7011	–	–
$\omega(1)$	19.9214	5.1412	–	–
α_1	1.0455	0.4705	2.222	0.026
$\|dCDS_{t-1}\|$	4.3104	2.3840	1.808	0.071
Student's t d.f.$^{(1/2)}$	1.5634	0.0814	–	–
$P(0\|0)$	0.9927			
$P(0\|1)$	0.0073			

Note: The influence of the lagged change of the sCDS spread is observed both in mean and variance, in both regimes. However, in the case of the mean equation, in the low-variance regime the impact is perceived faster and is positive, while in the high-variance one it is negative and perceived after two periods. Thus, we can conclude that together with the regime change, the character of relationships changes as well.

Table 8: ARMA-MS-EGARCH coefficients – Spanish bond spread

	Coefficient	Std.Error	t-value	t-prob
$dBond_{t-1}(0)$	0.2320	0.0399	5.8120	0
$dBond_{t-1}(1)$	0.1890	0.0417	4.5310	0
$\ln(\omega)(0)$	2.3657	0.6858	–	–
$\ln(\omega)(1)$	1.4849	3.2745	–	–
$P(0\|0)$	0.9991	–	–	–
$P(0\|1)$	0.0230	–	–	–
EGARCH α_1	0.1250	0.0350	3.5720	0
EGARCH β_1	0.8510	0.0490	17.3200	0
Student degrees of freedom$^{(1/2)}$	1.7021	0.1228		

The γ_1 was assumed to be equal to 0.

Table 9: MS-ARMA model coefficients – Greek CDS spread

	Coefficient	Std.Error	t-value	t-prob
$dCDS_{t-1}(0)$	0.006	0.013	4.500	0.000
$dCDS_{t-1}(1)$	0.003	0.001	4.950	0.000
$dCDS_{t-1}(2)$	-0.125	0.088	-1.410	0.159
$dCDS_{t-2}(0)$	-0.001	0.010	-0.051	0.960
$dCDS_{t-2}(1)$	-0.022	0.000	-59.200	0.000
$dCDS_{t-2}(2)$	0.173	0.094	1.850	0.065
$dCDS_{t-3}(0)$	-0.149	0.011	-13.100	0.000
$dCDS_{t-3}(1)$	0.011	0.000	42.700	0.000
$dCDS_{t-3}(2)$	0.193	0.113	1.710	0.088
$dCDS_{t-4}(0)$	0.010	0.008	1.260	0.209
$dCDS_{t-4}(1)$	-0.004	0.001	-5.730	0.000
$dCDS_{t-4}(2)$	0.672	0.133	5.040	0.000
$dCDS_{t-5}(0)$	0.027	0.006	4.310	0.000
$dCDS_{t-5}(1)$	0.008	0.001	9.960	0.000
$dCDS_{t-5}(2)$	-0.004	0.119	-0.032	0.975
$dBond_{t-1}(0)$	0.122	0.031	3.940	0.000
$dBond_{t-1}(1)$	0.012	0.004	3.040	0.002
$dBond_{t-1}(2)$	1.013	0.778	1.300	0.193
$dBond_{t-2}(0)$	0.111	0.032	3.450	0.001
$dBond_{t-2}(1)$	0.017	0.003	4.900	0.000
$dBond_{t-2}(2)$	0.895	0.771	1.160	0.246
$dBond_{t-3}(0)$	0.129	0.028	4.650	0.000
$dBond_{t-3}(1)$	-0.007	0.003	-2.580	0.010
$dBond_{t-3}(2)$	-0.864	0.839	-1.030	0.304
$dBond_{t-4}(0)$	0.138	0.044	3.150	0.002
$dBond_{t-4}(1)$	0.012	0.003	4.320	0.000
$dBond_{t-4}(2)$	-0.113	0.734	-0.154	0.877
$dBond_{t-5}(0)$	-0.051	0.027	-1.900	0.058
$dBond_{t-5}(1)$	-0.012	0.002	-5.860	0.000
$dBond_{t-5}(2)$	0.860	0.948	0.907	0.365
$dBond_{t-6}(0)$	0.075	0.027	2.780	0.005
$dBond_{t-6}(1)$	-0.015	0.003	-5.890	0.000
$dBond_{t-6}(2)$	-1.792	0.958	-1.870	0.062
$\omega(0)$	17.740	0.902	19.700	0.000
$\omega(1)$	0.625	0.052	12.000	0.000
$\omega(2)$	595.805	37.800	15.800	0.000
$P(0\|0)$	0.731	0.024	31.000	0.000
$P(1\|0)$	0.200	0.021	9.520	0.000
$P(0\|1)$	0.325	0.031	10.500	0.000
$P(1\|1)$	0.650	0.032	20.600	0.000
$P(0\|2)$	0.284	0.052	5.470	0.000
$P(1\|2)$	0.066	0.024	2.730	0.006

Note: Regime 2 is the one of the higher variance. In this regime all of the relationships between the CDS and bond spreads were broken, and the current value of CDS depended only on its own value four days before.

Table 10: MS-ARMA model coefficients – Italian CDS spread

	Coefficient	Std.Error	t-value	t-prob
$dCDS_{t-1}(0)$	-0.01749	0.01164	-1.502	0.133
$dCDS_{t-1}(1)$	0.14298	0.07013	2.039	0.042
$dCDS_{t-2}(0)$	-0.02117	0.01366	-1.549	0.122
$dCDS_{t-2}(1)$	0.01803	0.06711	0.269	0.788
$dCDS_{t-3}(0)$	0.01852	0.02071	0.894	0.371
$dCDS_{t-3}(1)$	-0.18725	0.07079	-2.645	0.008
$dBond_{t-1}(0)$	0.03298	0.03051	1.081	0.28
$dBond_{t-1}(1)$	0.13207	0.07717	1.711	0.087
$dBond_{t-2}(0)$	-0.00555	0.01831	-0.303	0.762
$dBond_{t-2}(1)$	-0.13836	0.07223	-1.916	0.056
$\omega(0)$	0.9318	0.2471	–	–
$\omega(1)$	12.504	0.351	–	–
$P(0\|0)$	0.76507			
$P(0\|1)$	0.13575			

Note: The relationships between CDS and bond spread are barely significant in the high-variance regime (the insignificant values are put in italics). The model outperformed the pure ARMA-GARCH model, as well as the ARMA-MS one.

Table 11: MS-ARFIMA-GARCH(1,1) model coefficients – Portuguese CDS spread

	Coefficient	Std.Error	t-value	t-prob
$dBond_{t-1}(1)$	1.6151	0.7190	2.2460	0.0250
Arfima d(t-1)(0)	0.0825	0.0374	2.2080	0.0270
Arfima d(t-1)(1)	0.6290	0.7578	0.8300	0.4070
$\omega(0)$	0.0825	0.0374	2.2080	0.0270
$\omega(1)$	2.7577	2.1053	–	–
α_1	0.2208	0.0405	5.4510	0.0000
β_1	0.7624	0.0348	21.9400	0.0000
$P(0\|0)$	0.9090			
$P(0\|1)$	0.9570			

Note: The low-variance regime is the absorbing one. In the high-variance regime, the long memory effect disappears

Table 12: Markov-Switching + GARCH(1,1) model coefficients – Spanish CDS spread

	Coefficient	Std.Error	t-value	t-prob
$dBond_{t-1}(0)$	0.14493	0.03074	4.715	0
$dBond_{t-1}(1)$	0.27478	0.10431	2.634	0.009
$dBond_{t-2}(0)$	-0.11082	0.05911	-1.875	0.061
$dBond_{t-2}(1)$	-0.01424	0.08339	-0.171	0.864
$dBond_{t-3}(0)$	-0.01716	0.0436	-0.394	0.694
$dBond_{t-3}(1)$	-0.14264	0.06003	-2.376	0.018
$dCDS_{t-1}(0)$	0.28459	0.13138	2.166	0.03
$dCDS_{t-1}(1)$	-0.01469	0.10621	-0.138	0.89
$\omega(0)$	0.84803	0.0806	–	–
$\omega(1)$	10.5183	0.6287	–	–
α_1	0.3575	0.13028	2.744	0.006
β_1	0.824	0.053	15.64	0
$P(0\|0)$	0.88208			
$P(0\|1)$	0.070814			

Table 13: MS-ARMA-PARCH – Czech Bond spread

	Coefficient	Std.Error	t-value	t-prob
$dCDS_{t-1}(0)$	-0.0237	0.0567	-0.418	0.676
$dCDS_{t-1}(1)$	0.6933	0.2464	2.813	0.005
$dBond_{t-1}(0)$	0.0013	0.0359	0.035	0.972
$dBond_{t-1}(1)$	-0.4918	0.2165	-2.272	0.023
$dBond_{t-2}(0)$	-0.0350	0.0326	-1.072	0.284
$dBond_{t-2}(1)$	0.5140	0.2386	2.154	0.031
$\omega(0)$	1.9017	0.5523	–	–
$\omega(1)$	4.6056	1.8632	–	–
α_1	0.0725	0.029	2.5	0.013
β_1	0.8961	0.0457	19.603	0
δ	1.3447	0.2884	–	–
$P(0\|0)$	0.9475			
$P(0\|1)$	0.7262			

Note: The low-variance regime is the absorbing one. Although the process remained almost all of the time in the low-variance regime, this model outperformed the pure PARCH model. Interdependence between the bond and CDS changes were observed only in the high-volatility regime.

Table 14: Markov-Switching ARMA(1,0) + ARCH(1) model coefficients – Hungarian Bond spread

	Coefficient	Std.Error	t-value	t-prob
$dCDS_{t-1}(0)$	0.2146	0.0627	3.424	0.001
$dCDS_{t-1}(1)$	0.2808	0.1079	2.602	0.009
$dCDS_{t-2}$**(0)**	**-0.0270**	**0.0717**	**-0.377**	**0.706**
$dCDS_{t-2}(1)$	-0.1569	0.0926	-1.694	0.09
$dBond_{t-1}$	0.0632	0.038	1.651	0.099
$\omega(0)$	8.9767	0.5273	–	–
$\omega(1)$	26.576	1.562	–	–
$P(0\|0)$	0.9717	–	–	–
$P(0\|1)$	0.05855	–	–	–
α_1	**0.0657**	**0.0453**	**1.447**	**0.148**

Note: The model was compared with ARMA-MS model and ARMA-GARCH model. Although the Schwarz criterion favored the model without the GARCH part over the ARMA-MS-ARCH one, adding even the insignificant ARCH parameter allowed for explaining the non-linear dependencies in the data.

Table 15: Markov-Switching + ARMA-GARCH model coefficients – Polish Bond spread

	Coefficient	Std.Error	t-value	t-prob
$dBond_{t-1}(0)$	0.9984	0.0016	612.5380	0.0000
$dBond_{t-1}(1)$	0.9997	0.0016	636.7730	0.0000
$dCDS_{t-1}(0)$	0.0514	0.0585	0.8780	0.3800
$dCDS_{t-1}(1)$	-0.0510	0.0372	-1.3700	0.1710
$\omega(0)$	3.6548	0.5424	–	–
$\omega(1)$	6.1439	1.1752	–	–
α	0.0697	0.0230	3.0300	0.0020
β	0.8845	0.0346	25.5940	0.0000
Student's t d.f.$^{(1/2)}$	2.9492	0.4326	–	–
$P(0\|0)$	0.9969			
$P(0\|1)$	0.0039			

Note: dCDS value insignificant in both regimes

Table 16: MS-ARMA-GARCH(1,0) model coefficients – French bond spread

	Coefficient	Std.Error	t-value	t-prob
$dBond_{t-1}(0)$	0.3593	0.0514	6.985	0
$dBond_{t-1}(1)$	0.2321	0.0993	2.338	0.02
$dCDS_{t-3}(0)$	-0.0002	0.0227	-0.007	0.994
$dCDS_{t-3}(1)$	-0.1519	0.0594	-2.557	0.011
d-ARFIMA	-0.1776	0.0477	-3.728	0
$\omega(0)$	1.34714	0.1089	–	–
$\omega(1)$	7.21464	0.722	–	–
$\alpha(0)$	0.3722	0.1164	3.198	0.001
$\alpha(1)$	0.5623	0.2202	2.554	0.011
$dCDS^2_{t-1}(0)$	0.1443	0.0564	2.559	0.011
$dCDS^2_{t-1}(1)$	0.0127	0.1039	0.122	0.903
$P(0\|0)$	0.9993			
$P(0\|1)$	0.0013			

Note: Dependencies in mean are observed in high-variance regime, while in volatility - in the low-variance one.

Table 17: MS-ARMA-GARCH(1,0) model coefficients – Finnish bond spread

	Coefficient	Std.Error	t-value	t-prob
$dCDS_{t-1}(0)$	0.1255	0.0784	1.6010	0.1100
$dCDS_{t-1}1)$	0.2201	0.0418	5.2710	0.0000
$dBond_{t-1}(0)$	0.1256	0.0486	2.5820	0.0100
$dBond_{t-1}(1)$	0.1397	0.0535	2.6130	0.0090
$\omega(0)$	1.0935	0.1600	–	–
$\omega(1)$	2.4470	0.3489	–	–
$\alpha(1)$	0.5649	0.2288	2.4690	0.0140
Student's t d.f.$^{(1/2)}$	1.6218	0.0772	–	–
$P(0\|0)$	0.9936			
$P(0\|1)$	0.0072			

Note: Broken dependencies in the low-variance regime.

Table 18: MS-ARMA model coefficients – Dutch EUR CDS spread

	Coefficient	Std.Error	t-value	t-prob
$dCDS_{t-1}(0)$	0.02512	0.05457	0.46	0.645
$dCDS_{t-1}(1)$	-0.52437	0.09754	-5.376	0
$dCDS_{t-2}(0)$	0.0092	0.02409	0.382	0.703
$dCDS_{t-2}(1)$	-0.50359	0.1093	-4.607	0
$dCDS_{t-4}(0)$	0.02137	0.01635	1.307	0.191
$dCDS_{t-4}(1)$	-0.32348	0.12251	-2.64	0.008
$dCDS_{t-5}(0)$	-0.02285	0.02464	-0.927	0.354
$dCDS_{t-5}(1)$	0.07643	0.11074	0.69	0.49
$dCDS_{t-6}(0)$	-0.02591	0.01565	-1.656	0.098
$dCDS_{t-6}(1)$	-0.18017	0.10606	-1.699	0.09
$dBond_{t-1}(0)$	0.0814	0.0312	2.609	0.009
$dBond_{t-1}(1)$	0.45246	0.18813	2.405	0.016
$dBond_{t-2}(0)$	-0.08269	0.02802	-2.951	0.003
$dBond_{t-2}(1)$	0.43778	0.20014	2.187	0.029
$dBond_{t-3}(0)$	-0.08249	0.02512	-3.284	0.001
$dBond_{t-3}(1)$	-0.09	0.14346	-0.627	0.531
d-ARFIMA	0.02091	0.051	0.41	0.682
$\omega(0)$	1.17454	0.0686	–	–
$\omega(0)$	9.45882	0.9711	–	–
$P(0\|0)$	0.93638			
$P(0\|1)$	0.19618			

Note: Although the model does not explain the non-linear dependencies in the data, it outperformed the pure GARCH model, as well as MS-GARCH one. The long memory parameter proved to be insignificant, yet including it in the model improved its explanatory power.