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A Dynamic Analysis of the Determinants of Greek Credit Default Swaps

By Maria do Rosario CORREIA [a†] Christian GOKUS [b]
Andrew Hughes HALLETT [c] & Christian R. RICHTER [d]

Abstract. There is a consensus in finance literature that credit default swap spreads can be used to calculate the default probability of a government bond. The question is therefore what determines the credit default swap spreads and also what is a good indicator that predicts the future behaviour of this security spreads. In this paper, we investigate several variables which have been used in the past to predict the CDS spreads. We do this by analysing the behaviour of credit swaps spreads of Greek sovereign debt over the recent financial crisis. We take into account the changes on the data generating process as the crisis evolves. Moreover, we also investigate which part of the dynamic process of CDS spreads is explained by each possible determinant. In order to do so, we use a time-frequency approach. As it turns out, some determinants are better in explaining the short term behaviour of the CDS spreads whilst others explain the long term behaviour. We can also say by how many months one factor determines the behaviour of the CDS spreads for Greek sovereign debt. With this information we are able to determine the probability of default and what it depends upon..
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JEL. C22, C58, G14, G15, H63, H68.

1. Introduction

The recent economic and financial crises highlighted the need to understand the nature of sovereign debt riskand in particular what determines its credit risk over time. Traditional models using time series stationary tests (see e.g. Bravo & Silvestre (2002), Alfonso (2005), Greiner, Koller, & Semmler (2007), Correia, Neck, Panagiotidis, & Richter (2008), amongst others) failed to explain the volatility in sovereign debt markets which calls for the use of models that

[a†] German University in Cairo, Egypt.
☎. 0020-2275899908
✉. maria.correia@guc.edu.eg
[b] University of Duisburg-Essen, Department of Economics, Germany.
☎. 0049-201-183-2276
✉. christian.gokus@uni-due.de
[c] George Mason University, School of Public Policy, Washington, D.C. USA.
☎. 001-703-993-9123
✉. ahughesh@gmu.edu
[d] German University in Cairo, Egypt.
☎. 0020-227582269
✉. Christian.richter@guc.edu.eg

include other market volatility drivers and market sentiment. In this study, we use credit default swap spreads as an indicator of changes in sovereign credit risk and we aim to determine the factors that drive spread changes.

Credit default swaps (CDS) are financial derivative contracts that are in essence similar to insurance contracts. To this extent, the buyer pays a fee - *CDS spread* - to the seller to be compensated on the occurrence of a specified credit event. Typically, such a credit event occurs when the issuer defaults or restructures its debt.

Thus, according to Grossman & Hansen (2010) credit default swap spreads, along with other indicators such as bond and equity price information, have become crucial instruments for risk analysis[i]. These authors highlight that CDS spreads reflect the market view of a credit event. Because they are updated frequently (e.g. daily), CDS spreads are valuable for the assessment of trading exposures, active portfolio management and the determination of credit conditions. According to the probability model a one-year CDS is priced according to the following formula:

$$P_{CDS} = (1-p)N(1-R)\delta \tag{1.1}$$

where $P_{CDS}$is the price of the CDS, 1 -*p* is the default probability, *N* is the nominal value of the contract, *R* is recovery rate and δ is the discount rate. We are interested in determining the default probability. Solving eq (1.1) with respect to the the default probability we get:

$$\frac{P_{CDS}}{N(1-R)\delta} = 1-p \tag{1.2}$$

As can be seen from eq. (1.2) the default probability depends on the price of the CDS, the nominal value of the contract, the recovery rate and and the discount rate. Typically, an investor makes an assumption about the recovery rate (say 20%), takes it "insured" value to be the nominal value of the contract, and uses a discount rate (say the market rate) and the price of the CDS to determine the default probability. Hence, if we know what determines the CDS price, we can then determine the default probability or the credit risk of the underlying debt instrument.

Maltritz (2012) applied a Bayesian Model Averaging (BMA)[ii] to a annual panel data sample of sovereign yield spreads of EMU member states from 1999 to 2009 to examine the determinants of sovereign credit spreads. The sovereign yield spreads of EMU member states are calculated in relation to German bond yields observed in secondary markets. Maltritz (2012) provides evidence that country fiscal variables such as budget balance and government debt as well as external sector variables, such as terms of trade, trade balance and openess are likely to determine sovereign yield spreads. Additionally, global financing conditions, as measured by the US interest rate, and market sentiments, asindicated by corporate bond spreads, tend to influence sovereign yield spreads. Lemmen & Goodhart (1999) have argued, however, that inflation rate differentials play a significant role on sovereign default risk. This argument is further supported by Coudert, Couharde, & Mignon (2013) that suggest that one reason for the crisis in Greece after 2009 was the loss of competitiveness because of inflation differentials that could not be cancelled out by the possibility of devaluation (since Greece did not have its own currency).

Barbosa & Costa (2010) analyse sovereign credit yields for euro area countries from early 2007 to May 2010. Their evidence shows that prior the collapse of

Lehman Brothers, sovereign credit yields were mainly driven by global risk premium[iii]. As Alessandrini, Fratianni, Hallett, & Presbitero (2014) show, with the deepening of financial and economic crises, factors associated with market liquidity and country credit risk rapidly increased in importance. In early 2010, sovereign credit risk and a further increase in global risk premiums were the main drivers determining the evolution of euro area sovereign yields. This evidence is corroborated by other studies.[iv]

Focusing on the volatility of financial markets, behavioral finance theory has long argued that individual investors actions can cause securities market prices to deviate from their fundamentals. In this context, Daniel, Hirshleifer, & Teoh (2002) review a considerable number of studies that argue against the premises of efficiency market hypothesis. On one hand, Daniel et al. (2002) highlight recent theoretical research[v] that suggests that arbitrage by rational investors does not necessarily eliminate mispricing. On the other hand, these authors stress that empirical studies (e.g. Simon, 1955; Tversky & Kahneman, 1974; Hirshleifer, 2001; Cooper & Fazio, 1984) provide evidence that investors and analysts suffer from a general problem of credulity, not being able to discount apropriately the incentives for other parts of the market (e.g. firms, brokers, analysts and other investors) to manipulate available information. This is also in line with Statman (2008) that argues that one important factor of behavioural theory is that market participants are assumed to behave rationally but with a limited information set. Daniel et al. (2002) also suggest that government activism and readiness to bring coercise power into the markets is not necessarily helpful and can be severily harmful. These authors argue that politicians are not immune to biases and self-interests that alter their evaluations of the fundamental value of financial assets. To this extent, Daniel et al. (2002) suggest that investors education, market disclosure and reporting rules designed to make financial information consistent and easy to process can improve the efficiency of market prices.

Bruneau, Delatte, & Fouqueau (2014) use a second-generation model[vi] to analyse the influence of market sentiments on the sudden eruption of a crisis on the European sovereign markets. These authors concluded that not only self-fulfilling herd behaviour (together with fundamental factors) ignited the crisis in European markets, but also the sovereign Credit Default Swap (CDS) market served as a speculation mechanism to exacerbate the loss of value in the cash market (i.e. driving down the prices of sovereign bonds). The lack of regulation of CDS market together with the concentration of trades in a small number of dealers provides an incentive for price manipulation in CDS markets.

Noeth & Sengupta (2012) analysed the changes in spreads on five-year CDS in Europe from 2005 to 2012. They compare CDS spreads for four country groupings: distressed countries in the eurozone; other countries in the eurozone; Western European countries that do not use the euro as currency and Eastern European countries that do not use the euro as currency. These authors show that although prior the crisis CDS spreads of the distressed eurozone countries were even lower than their Eastern European peers (which have been severely affected by the Russian default in the late 1990's), the CDS spreads of the former countries have continued to rise, reaching newer highs each quarter between 2008 and 2012.So the question is why the CDS prices were "too" low prior to the Eurozone crisis. One obvious argument could be simple mispricing of risk (De Grauwe & Ji, 2013). However, as Alessandrini et al. (2014) show, raising external imbalances may also lead to an increase in the risk spreads.

As over the counter instruments, CDS allow transacting parties to avoid regulatory requirements imposed by more formal insurance arrangements. Specifically, sellers of CDS are not required to hold reserves against the probability of default of the underlying security. There is a consensus that the lack of regulation of CDS markets exarcebated the recent financial crisis (see e.g Noeth & Sengupta (2012) for lack of sellers' financial back up and Grady & Lee (2012) for sovereign overrule of contractual terms arguments).

The recent financial crisis in the Southern European countries seems to suggest that traditional explanatory variables failed to predict Greek debt default risk. This is important, because the financial markets lost confidence on Greek sovereign bonds before the countryactually defaulted. So we need to include in our model a proxy that may detect the change in market sentiment. A change in sentiment implies that the structure of the model has to change. It may be that variables which were not important before this change, suddenly become important or even more important, whilst other variables lose their significance.

The aim of this paper is therefore to detect variables which became more important as predicting factors at the dawn of the Greek financial crisis. In particular, we are looking for variables which explain the behaviour of the Greek one year credit default swap spreads. Moreover, we also analyse by how much time this variable is leading the CDS spreads. The lead time is important, because it gives us an idea how much time we have left when the indicator changes before the country in question may default. Our approach is therefore inductive.

As it turns out, the results are not black and white. We found variables which are good indicators for the long term behaviour of the CDS spreads, but not good indicators in the short term and vice versa. Moreover, our list of variables may actually not be comprehensive. We followed Maltritz (2012) who seemed to have used an consensual set of variables (see Appendix 1).

In order to conduct our analysis, we estimated single equation models in order to avoid mulitcollinearity. We estimated these models by using the Kalman filter aiming to catch structural changes. We then transferred the results into the frequency domain to calculate the lead-lag relationships between those variables and the CDS spreads. In this sense we followed Hughes Hallett & Richter (2004; 2006; 2011) who also transferred the time domain regression results into the frequency domain.

The paper is structured as follows: the next section will explain the regression method in great detail. The following section explains the frequency domain calculations. Section four presents the results and section 5 concludes.

2. Kalman Filter Regression

All the data collected was retrieved from Datastream/Thompson-Reuters and is made up of monthly data from 2005:1 to 2012:6. In some cases, we use growth rates (see below). These growth rates are then defined as follows for a monthly growth rate:

$$y_t = \Delta\left(\log\left(Y_t\right)\right) = \log\left(\frac{Y_t}{Y_{t-1}}\right) \tag{2.1}$$

Suppose we are interested in the relationship between two variables, $\{y_t\}$ and $\{x_t\}$ say, where $\{y_t\}$ is the CDS spreads and $\{x_t\}$ is a GDP growth rate. We assume that they are related in the following way:

$$V(L)_t\, y_t = A(L)_t\, x_t + u_t,\; u_t \sim \text{i.i.d.}\left(0, \sigma^2\right) \tag{2.2}$$

where A(L) and V(L) are filters, and L is the lag operator such that $Ly_t = y_{t-1}$. Eq. (2.2) is an autoregressive distributed lag model of the dimension (p,q)

(ARDL(p,q)). Notice that the lag structure, A(L) and V(L), is time-varying. That means we need to use a state space model (we use the Kalman filter) to estimate the implied lag structure. That is

$$
\begin{aligned}
v_{i,t} &= v_{i,t-1} + \varepsilon_{i,t},\ \text{for } i = 1, \dots, p \text{ and } \varepsilon_{i,t} \sim \left(0, \sigma^2_{\varepsilon_i}\right) \\
a_{i,t} &= a_{i,t-1} + \eta_{i,t},\ \text{for } i = 0, \dots, q \text{ and } \eta_{i,t} \sim \left(0, \sigma^2_{\eta_i}\right)
\end{aligned}
\qquad (2.3)
$$

In order to run the Kalman filter we need initial parameter values. The initial parameter values are obtained estimating them by OLS using the entire sample (see also Wells, 1996)[vii]. Given these starting values, we can then estimate the parameter values using the Kalman filter. We then employed a general to specific approach, eliminating insignificant lags using the strategy specified below. The maximum number of lags was determined by the Akaike Criterion (AIC), and was found to be nine in each case. Each time we ran a new regression we used a new set of initial parameter values. Then, for each regression we applied a set of diagnostic tests shown in the tables in Appendix 2, to confirm the specification found. The final parameter values are filtered estimates, independent of their start values.

Using the above specification implies that we get parameter values for each point in time. Hence, a particular parameter could be significant for all points in time; or at some but not others; or it might never be significant. The parameter changes are at the heart of this paper as they imply a change of the lag structure and a change in the spectral results. We therefore employed the following testing strategy: if a particular lag was never significant then this lag was dropped from the equation and the model was estimated again. If the AIC criterion was less than before, then that lag was completely excluded. If a parameter was significant for some periods but not others, it was kept in the equation with a parameter value of zero for those periods in which it was insignificant. This strategy minimised the AIC criterion, and leads to a parsimonious specification. Finally, we tested the residuals in each regression for auto-correlation and heteroscedasticity.

The specification (2.2) – (2.3) was then *validated* using two different stability tests. Both tests check for the same null hypothesis against differing temporal instabilities. The first is the fluctuations test of Ploberger, Kramer, & Kontrus (1989), which detects *discrete* breaks at any point in time in the coefficients of a (possibly dynamic) regression. The second test is due to LaMotte & McWhorter (1978), and is designed specifically to detect *random* parameter variation of a specific unit root form (our specification). We found that the random walk hypothesis for the parameters was justified for each variable (results available on request). Finally, we chose the fluctuations test for detecting structural breaks because the Kalman filter allows structural breaks at any point and the fluctuations test is able to accommodate this.[viii] Thus, and in contrast to other tests, the fluctuations test is not restricted to any pre-specified number of breaks.[ix]

Once this regression is done, it gives us a time-varying ARDL(p,q) model. From this ARDL(p,q) we can *calculate* the Fourier transform, in order to calculate the time-varying gain and phase shift. The basic idea is to find the phase shift of a signal x(t), at time t, by analysing a small portion of the signal around that time.

3. The Phase Shift and Gain

Having estimated the coefficients in (2.3), we can calculate the gain and the phase shift. That allows us to overcome a major difficulty in this kind of analysis: namely that a very large number of observations would usually be necessary to carry out the necessary frequency analysis by direct estimation. This may be a particular problem in the case of structural breaks, since the sub-samples would typically be too small to allow the associated spectra to be estimated directly.

In Hughes Hallett & Richter (2002; 2003a; 2003b; 2004) we use the fact that the time-varying cross spectrum, $f_{YX}(\omega)_t$, using the Fast Fourier Transform is given by

$$f_{YX}(\omega)_t = |A(\omega)|_t \, f_{XX}(\omega)_t \tag{3.1}$$

where $A(\omega)$ is the gain which is calculated using the Fast Fourier transform of the weights $\{a_j\}_{j=-\infty}^{\infty}$. As noted above, the traditional formulae can be used to do this at each point in time. The last term in (3.1), $f_{XX}(\omega)_t$, is the spectrum of the predetermined variable. Hence this spectrum may be time varying as well. Next, we calculated the gain according to

$$|A(\omega)|_t = \left| \sqrt{\left(\frac{\sum_{b=1}^{q} a_{b,t} \exp(-j\omega b)}{1 - \sum_{i=1}^{p} v_{i,t} \exp(-j\omega i)} \right)^2} \right|_t \text{, for b=1...q and i=1...p} \tag{3.2}$$

which is time-varying as well.

To distinguish changes in timing from changes in the importance of different cycles, we need to measure the phase shift between x_t and y_t. To do that, we need the *phase angle*. The phase angle measures the lead or lag relationship between two variables at each cyclical frequency. Formally:

$$\varphi(\omega) = \tan^{-1} \frac{-Q_{YX}(\omega)}{C_{YX}(\omega)} \tag{3.3}$$

where $C_{YX}(\omega) = f_{XX}(\omega) \sum_{j=0}^{\infty} a_j \cos \omega j$, and $Q_{YX}(\omega) = f_{XX} \sum_{j=0}^{\infty} a_j \sin \omega j$.(3.4)

The phase angle can therefore be written as

$$\varphi(\omega) = \tan^{-1} \left(\frac{\sum_{j=0}^{\infty} a_j \sin \omega j}{\sum_{j=0}^{\infty} a_j \cos \omega j} \right) \tag{3.5}$$

Hence, to calculate the phase angle, all we need to know are the coefficients a_j. However, in this paper we analyse a “standardised” phase angle, or *phase shift*:

$$\tau(\omega) = \frac{\varphi(\omega)}{\omega} \tag{3.6}$$

To see how to interpret the phase shift statistic, consider the following figure:

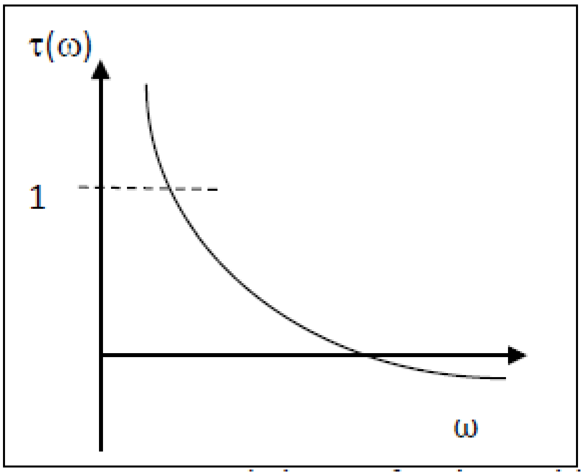

Figure 1. Assumed Shape of a Phase Shift

Figure 1 shows one variable is following the other at long cycles, with a delay of one quarter – peak to peak say. But for smaller cycles the delay is shorter. In efficient markets, the two processes should follow each other very closely, since agents are able to process new information relatively quickly. But in other cases there will be natural leads and lags depending on the production structure and degree of vertical integration.

The formulae given above are for the time-invariant case. Since we get new values for $a_j$for each point of observation t, we can apply the above formulae for every point t. In other words the time-varying phase shift changes to:

$$\tau(\omega)_t = \frac{\varphi(\omega)_t}{\omega} \tag{3.7}$$

In the next section we present the time domain results and the time-varying phase shifts.

4. Empirical Results

In this section, we present the empirical results. As mentioned above all regressions are monthly regressions from 2005:1 to 2012:6. The data are fitted to an ARDL(p,q) model as described above, and tested for stationarity, statistical significance, and a battery of diagnostic and specification checks before being converted to the spectra and cross-spectra that we need. For each point in time we obtain a complete set of regression results which gives 90 results for each variable. In the appendix, we only give the regression result of the last point in time (2012:6). As the time domain regression results and tests are rather extensive, they are available from the authors on request.

4.1. Gross Fixed Capital Formation

The first variable we checked was Gross Fixed Capital Formation (GFCF). GFCF serves as an indicator for investments and may give an idea about sentiment for growth of the economy and hence its ability to serve its debt. The regression resulted in ARDL(7,2) model (see appendix 2). The calculated phase shift is shown in figure 2 below.

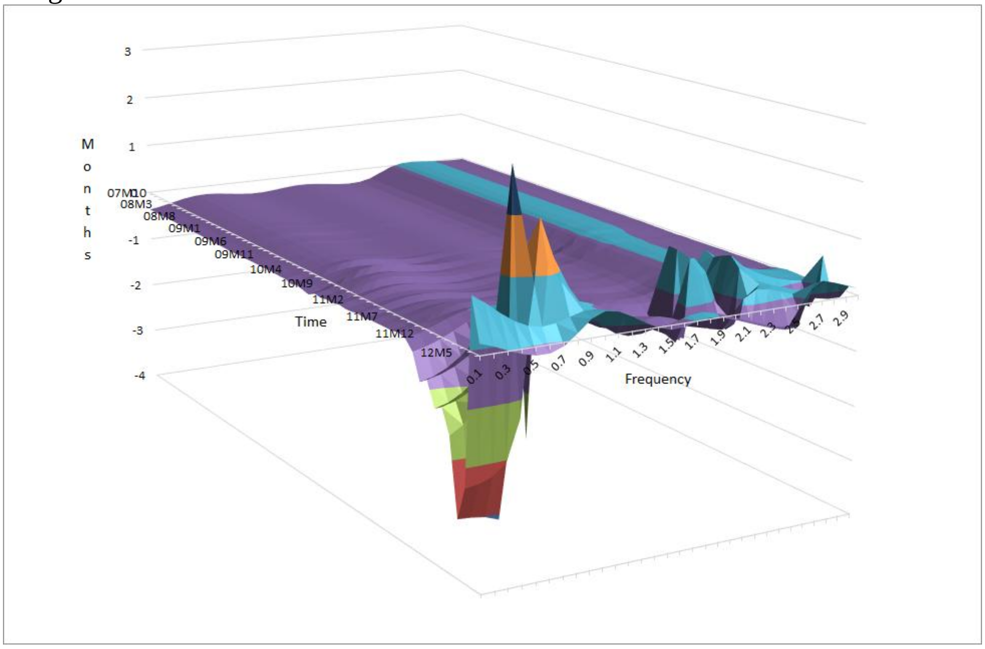

Figure 2. *The Phase Shift for CDS spreads and GFCF*

The above figure shows that GFCF has always been leading CDS spreads from the beginning of the sample. However, this lead increases especially for the long run trend from less than a month to about 4 months. Just at the end of the sample this lead reverted to a lag of about 1 month.

When it comes to the shorter term behaviour, the CDS spreads lead short term variations in investmentby less than a month, 3-month cycles by 1 month and 9-month cycles by up to 3 months although this was reduced to about one month at the end of the sample.

The figure also shows what we claimed above, namely that the financial crisis changed the lead-lag relationships between variables. By contrast, it is obvious that the link between the two variables was stable prior to the crisis with very little volatility.

This result of our analysis is that the use of GFCF as an indicator is fairly limited. One may use it as to determine the CDS spreads in the long run, but not necessarily for the short run, although it leads the CDS spreads for 2.4-month cycles by about one month.

4.2. Current Account

The following figure shows the phase shift between CDS spreads and the current account. Figure 3 is based on ARDL(6,7) model (appendix 2).

Figure 3 shows that the lead-lag relationship between the CDS spreads and the current account isstable until the financial crisis. Both variables were in phase prior to the crisis. The crisis then caused a lead for the current account of 6 months at the long run trend. Any other cycles remained in phase apart from the 12 month cycle where the CDS spreads were leading by one month. Towards the end of the sample the CDS spreads and the current account were back in phase, probably indicating that the financial crisis had been fully incorporated in the data sothat the link between the two variables returned to the pre-crisis state.

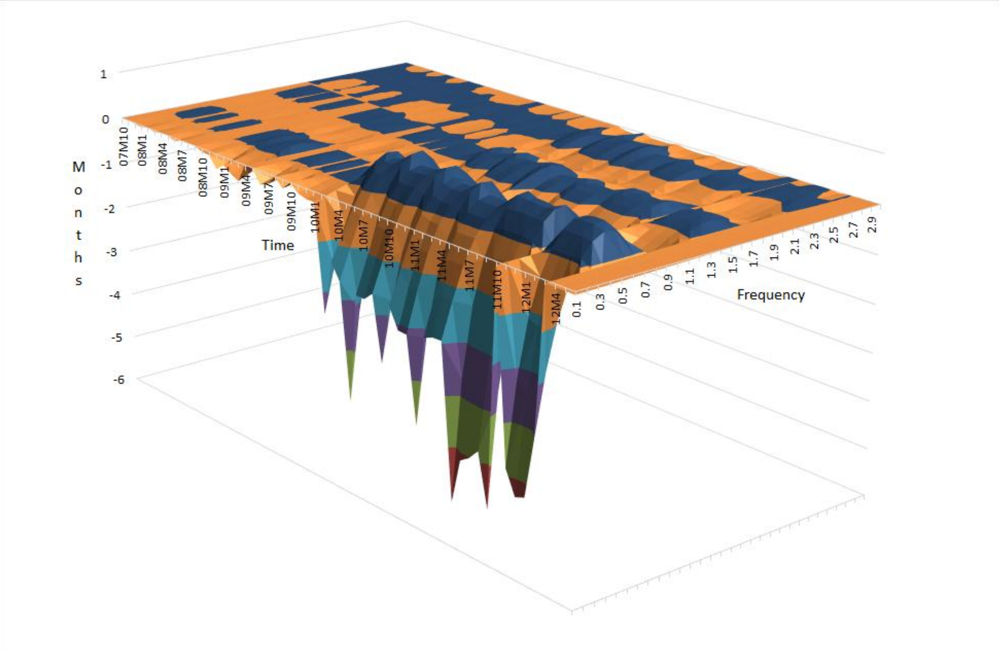

Figure 3. *Phase Shift between CDS spreads and Current Account*

As a result, the current account can serve as an indicator of future CDS spreads behaviour for the long run trend. An increase in the lead of the current account for the long run trend of the CDS spreads could indicate a crisis to come and likewise the disappearance may indicate that the crisis is over. However, the current account does not allow to make inferences concerning the short term behaviour as both variables would react to events at the same time. The time domain results are shown in appendix 2 in table 2.

4.3. Deficit to GDP Ratio

The deficit to GDP ratio is one of the "obvious" variables as it is mentioned in the Maastricht treaty which is meant to prevent a country defaulting on its debt. The regression is based on an ARDL(6,6) model (see appendix 2, table 3). Figure 4 below shows the phase shift between CDS spreads and the deficit to GDP ratio. As in the previous cases the financial crisis changes the lead-lag relationship. The problem is that the phase shift shows already a high volatility prior to the financial crisis, namely 2 years after the occurrence of the global financial crisis, where the volatility was even bigger than for the Greek financial crisis. This makes it difficult to use the deficit to GDP ratio as an indicator for a Greek financial crisis. Despite this, the deficit to GDP ratio has the advantage that it is leading CDS spreads for most frequencies for up to 5 months during the Greek crisis. In the short run, this lead is only 1 month though. This lead is quite robust when it re-emerged in 2010:07 and was stable until the end of the sample. However, it does not give an as clear a picture of events still in the future as does the current account.

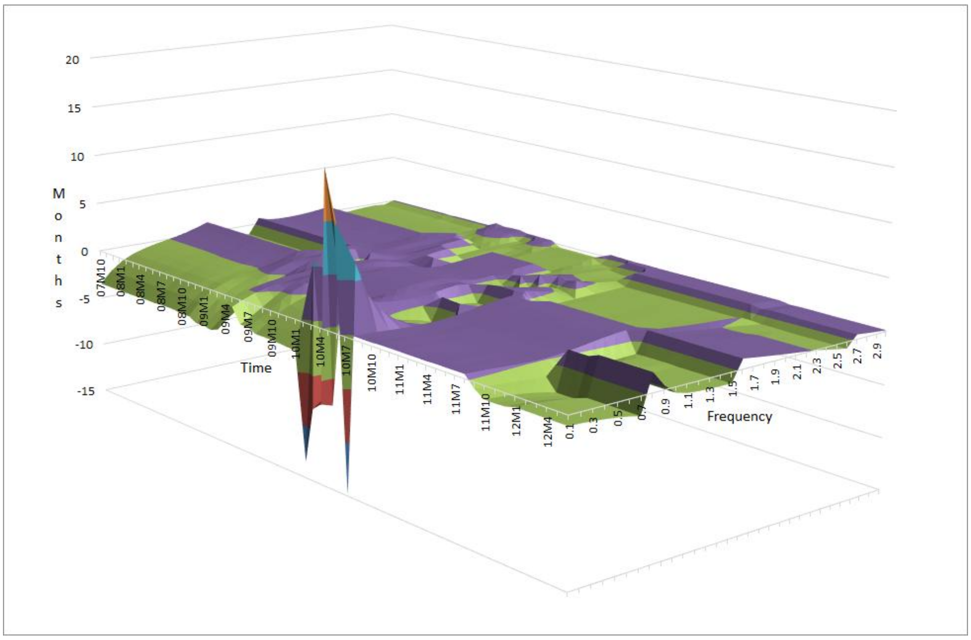

Figure 4. *Phase Shift between CDS spreads and Deficit to GDP Ratio*

4.4. Annualised GDP Growth Rate

In order to analyse the impact of GDP on CDS spreads we have tried the level GDP as well as several GDP growth rates (monthly, annual). It turned out that the annualised growth rate explained CDS spreads best (in terms of lowest Akaike criterion). For this reason we only report the results for the annualised GDP growth rate. The estimated equation is based on an ARDL(6,5) model (table 4 in appendix). The figure below shows the phase shift between CDS spreads and annualised GDP growth (figure 5).

Figre 5 shows that the financial crisis led to big shifts in the lead-lag relationship. While the CDS spreads and GDP growth were in phase before the crisis, the financial crisis itself caused CDS spreads to lead GDP by up to 0.35 months. Hence, GDP is not a good indicator of shifts in spreads because it is either coincident with or follows the CDS spreads. However, given the scale of the change, the change itself can be seen as indicator of a crisis to come. In other words, if the CDS spread decouples itself from the GDP, then there may be a problem coming up.

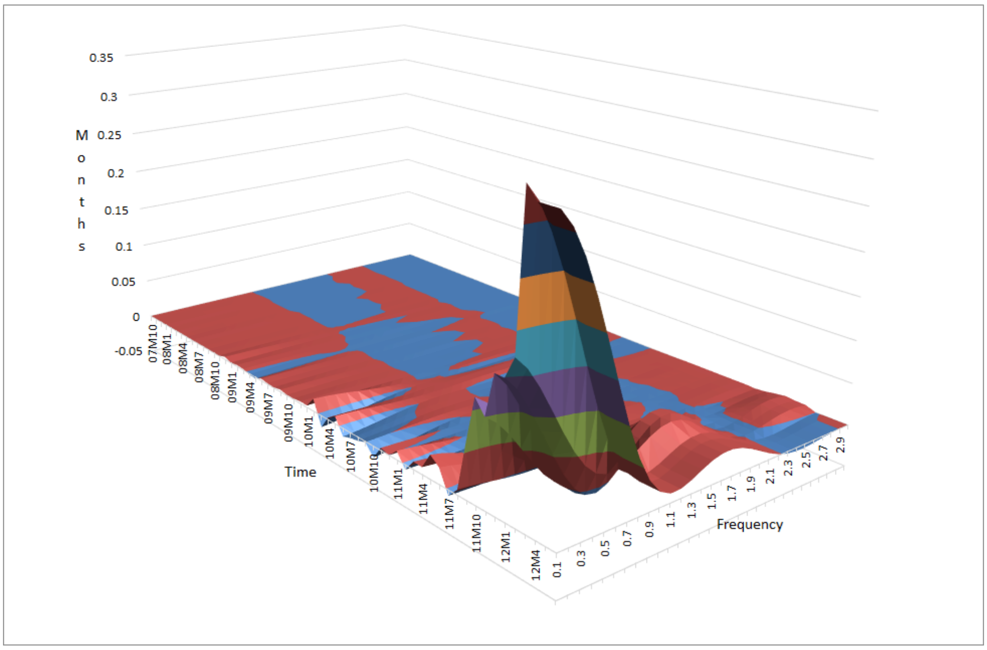

Figure 5. *Phase Shift CDS spreads – Annualised GDP Growth Rate*

4.5. Capital Utilisation

An indicator related to GDP is capital utilisation. If labour markets were flexible then capital utilisation could lead the CDS spreads and indicate a problem in terms of future growth and therefore the country's ability to repay its debt. The estimated equation is an ARDL(6,4) model (see table 5 in appendix 2).

However, as figure 6 shows, the lead-lag relationship did not really change during the recent crisis. Apart from the long-run trend, CDS spreads and capital utilisation were in phase. For the trend capital utilisation leads by about half a month which did not really change during the recent crisis. The lead-lag relationship did change during the global financial crisis however, when capital utilisation increased its lead to up to 6 months. As it is sometimes a difficult task to identify a crisis or even when one country is in a crisis capital utilisation can serve as an indicator especially when one observes that the lead is increasing.

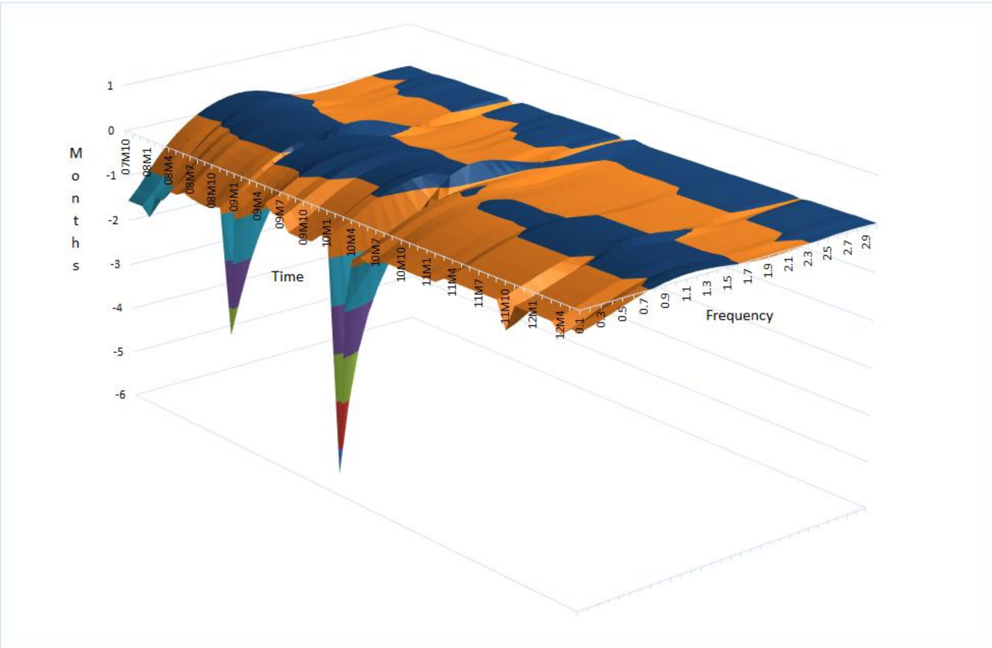

Figure 6. *Phase Shift CDS spreads – Capital Utilisation*

4.6. Inflation Rate

In this section we test the inflation rate. As the inflation may be driven by expectations as well as the CDS there could be a correlation. The estimated equation is based on an ARDL(6,4) model (see table 6 in appendix 2). Figure 7 shows the phase shift for CDS spreads and the inflation rate.

As can be seen from figure 7, as far as the long run behaviour of the CDS spreads is concerned the CDS spreads are leading the inflation rate by about 1 month. At the beginning of the sample it was up to 3 months. What makes the inflation rate interesting is that it is leading the CDS spreads at the short end by up to 0.25 months or 1 week. This is particularly true for the period after 2010 i.e. during and after the Greek financial crisis. Inflation is so far the only variable that is able to lead the CDS spreads in the short run. Albeit by only 1 week. The inflation rate also leads the CDS spreads for 5.7 months cycles by up to one month. The last property even increased during the financial crisis.

In summary, the inflation rate does not lead the CDS spreads for its long-run behaviour. But it does lead the CDS spreads for their short run behaviour.

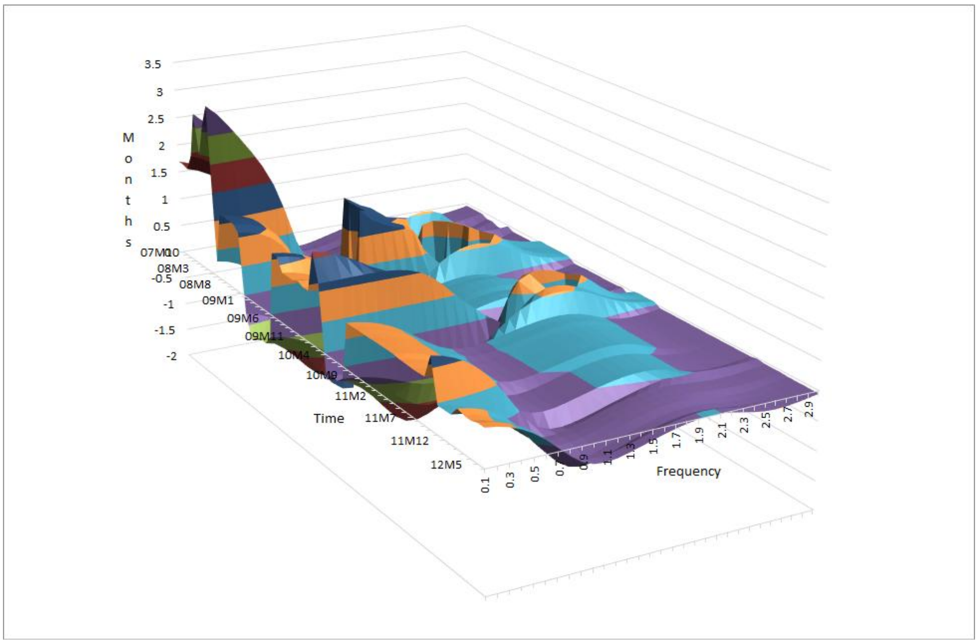

Figure 7. *Phase Shift CDS spreads – Inflation rate*

4.7. Debt to GDP Ratio

The debt to GDP ratio is another indicator from the Maastricht Treaty. For this reason it can be assumed that investors take the debt to GDP ratio into account. The estimated equation resulted in an ARDL(5,5) model (see table 7 in the appendix).

Figure 8 shows the phase shift between CDS spreads and the debt to GDP ratio. As before the financial crisis in Greece led to change of the lead-lag relationship. From the beginning of the sample CDS spreads are leading the GDP to debt ratio for the trend by 8 months. During the financial crisis this lead is reduced to 2 months. For most of the sample the CDS spreads were also leading the debt to GDP ratio by about four month cycles. The crisis however turns this lead into a lag of about 1 month. Remarkably the crisis also results in an increased lead of the debt to GDP ratio at 8-month cycles (in contrast to the trend) by about 3 months. For the remaining shorter cycles the financial crisis resulted in an in-phase relationship between the two variables despite the CDS spreads' leadership prior to the crisis.

In summary, the financial crisis led to an in-phase relationship for high frequencies, but a "mixed relationship" at low frequencies. In the long run the CDS spreads are leading whilst in the medium term the debt to GDP ratio is leading. Hence, the debt to GDP ratio may not necessarily serve as an indicator of a start of a crisis itself, but in the crisis it serves as an indicator of the direction in which CDS spreads are likely move in roughly 8 months time.

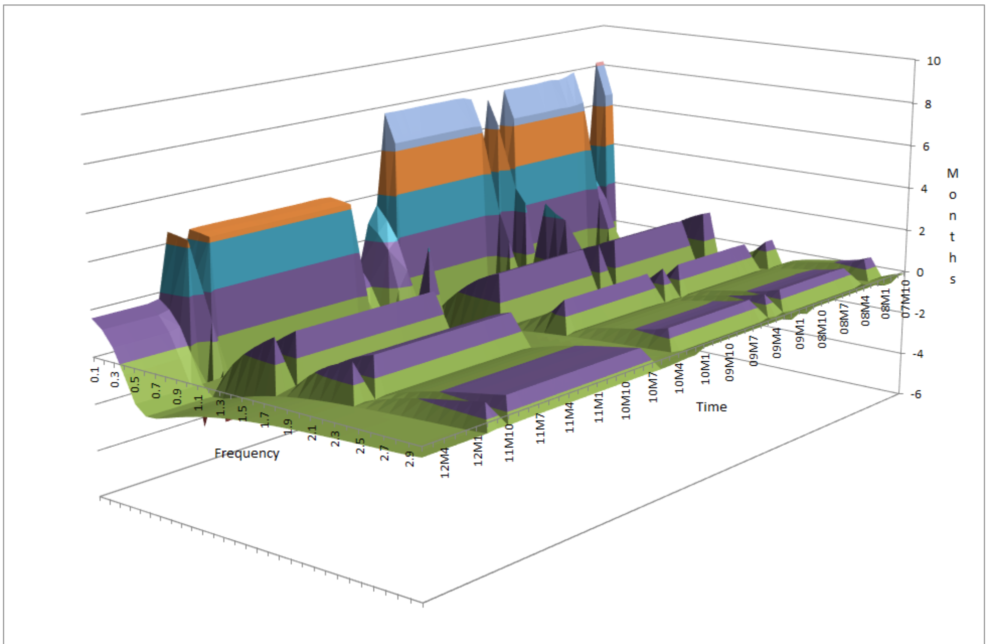

Figure 8. *Phase Shift CDS spreads – Debt to GDP Ratio*

4.8. Economic Sentiment Indicator

The Economic Sentiment Indicator (ESI) has been developed by the European Commission DGII(ECFIN). It is a composite indicator made up of five sectoral confidence indicators with different weights: Industrial confidence indicator, Services confidence indicator, Consumer confidence indicator, Construction confidence indicator, Retail trade confidence indicator. It is therefore designed to reflect as a leading indicator how the GDP may develop in the near future. Hence, the hypothesis is that investors may take into account the confidence of the above mentioned five sectors.

The estimated equation resulted in an ARDL(6,6) model (see table 8 in appendix 2). Figure 9 shows the phase shift between CDS spreads and the growth rate of the economic sentiment indicator. Although various events did lead to changes in the lead-lag relationship, as far as the Greek financial crisis is concerned, both CDS spreads and the indicator are in phase. Moreover, the economic sentiment indicator did not indicate the arrival of the crisis before 2011. As a result, the economic sentiment indicator is not really useful for predicting the behaviour of the CDS spreads.

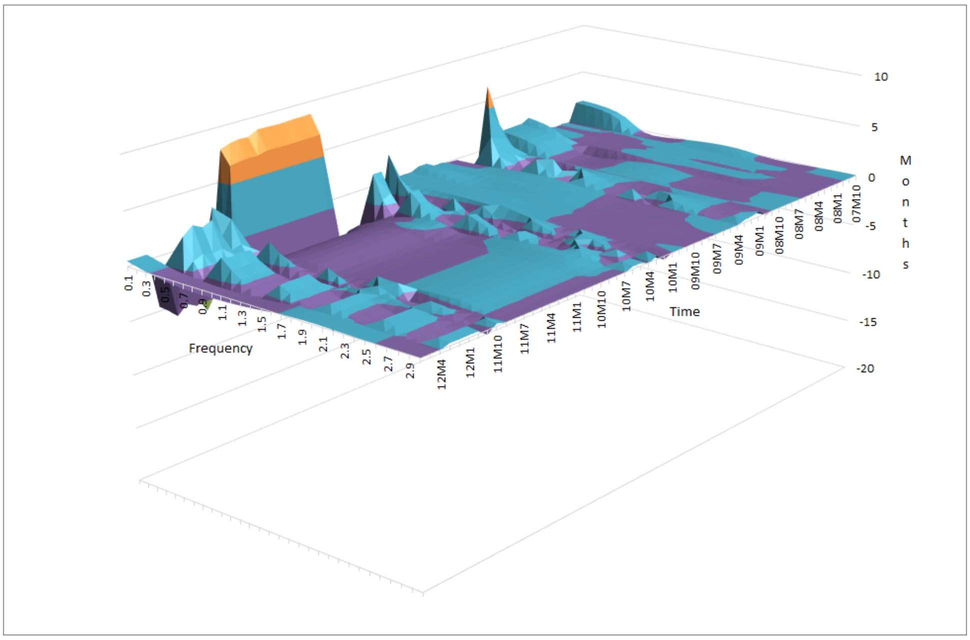

Figure 9: *Phase Shift CDS spreads – Economic Sentiment Indicator*

4.9. The S&P 500 index (SPX)

Standard and Poor's 500 Index is a capitalization-weighted index of 500 stocks. The index is designed to measure performance of the broad domestic economy through changes in the aggregate market value of 500 stocks representing all major industries. The hypothesis tested here is that if the Greek economy is globally connected then a change of the SPX should result in a change in the CDS spreads. The ARDL model estimated in this case is of dimension (6,3) as table 9 in appendix 2 shows.

Concerning the lead-lag relationship the SPX link to the CDS spreads does not change significantly when the Greek financial crisis starts as figure 10 shows. Since the beginning of the global financial crisis in 2007, the SPX shows a lead for short term cycles by up to one month. The SPX is therefore one of the few indicators that can be used to determine short term cycles of the CDS spreads. However, in terms of long term trend, the CDS spreads are leading the SPX by 1 month at the end of the sample. Apart from that, the SPX is leading the CDS spreads for 9-month cycles by 2 months. Last but not least the CDS spreads are leading the SPX for 5-month cycles by 1 month.

In summary the SPX is by definition determined mostly by events at the NSE and NASDAQ. However, for short term movements it may also be used to determine Greek CDS spreads movements, in particular, when the capital markets are very volatile and investors demand exceptionally high risk premium to invest in risky assets. For the long run the CDS spreads seem to lead the movements of SPX.

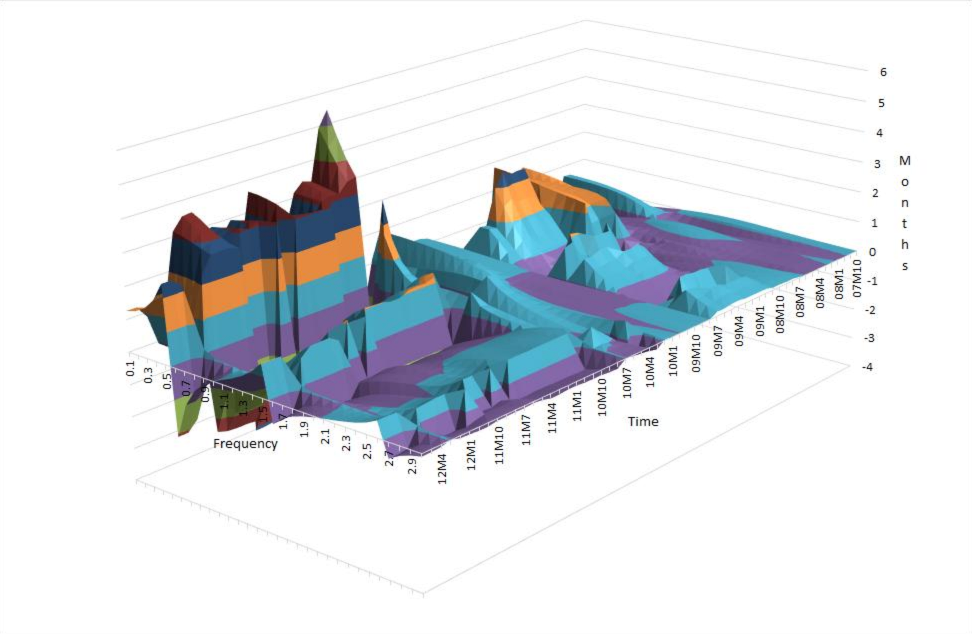

Figure 10: *Phase Shift CDS spreads – SPX*

4.10. US T-Bills

As with the SPX the hypothesis of using T-Bills is to check whether the Greek capital market is detached from the international capital market. Obviously, US T-Bills are not directly affected by troubles on the Greek capital market. But US T-Bills may serve as a safe haven if there is trouble elsewhere. We therefore regressed the CDS spreads on US T-Bills which resulted in an ARDL(7,7) model see table 10 in appendix 2.

Figure 11 shows the phase shift between CDS and US T-Bills. The impact of the Greek financial crisis is clearly visible. At the lower frequencies, the CDS spreads are leading. At higher frequencies, the T-Bills lead by up to 2 months. However, for the very short term cycles, this lead reduces to less than a month. And for lower frequencies/long cycles the CDS spreads lead by one month. The initial hypothesis is therefore confirmed. The lead-lag relationship between the two variables does change because of the weakening of the Greek capital markets in relation to the US one. Another feature is that before the Greek financial crisis the CDS spreads were leading the T-Bill or were in phase for most frequencies. The Greek financial crisis changed this. So it seems that if a small country goes into distress, the safe haven takes the lead at least for the short term. That hypothesis however, needs to be tested for more countries.

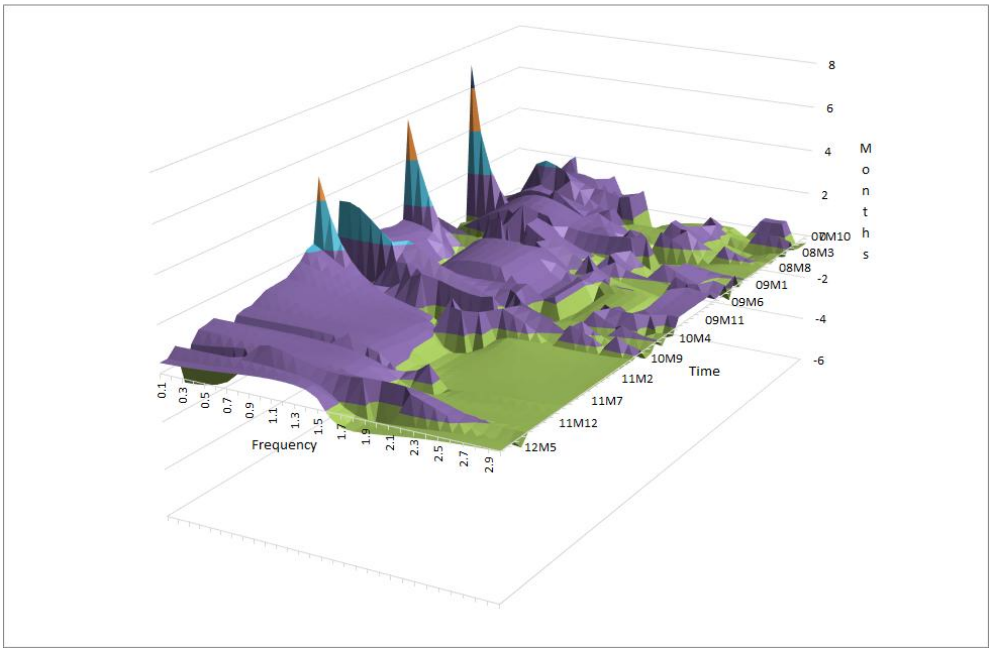

Figure 11: *Phase Shift CDS spreads – US T-Bills*

4.11. Unemployment Rate

The unemployment rate is the last macroeconomic variable we checked. Estimation of this relationship resulted in an ARDL(4,7) model as table 11 in appendix 2 shows. The impact of the Greek financial crisis is now clearly visible in figure 12.

However, the CDS spreads are leading the long run trend, whilst the unemployment rate leads 10-month cycles by 4 months. For higher frequencies both variables are in phase. Before the Greek financial crisis both variables were largely in phase. So the unemployment rate cannot be used to predict short term behaviour of the CDS spreads. Moreover, it does not serve as an indicator for the advent of a crisis.

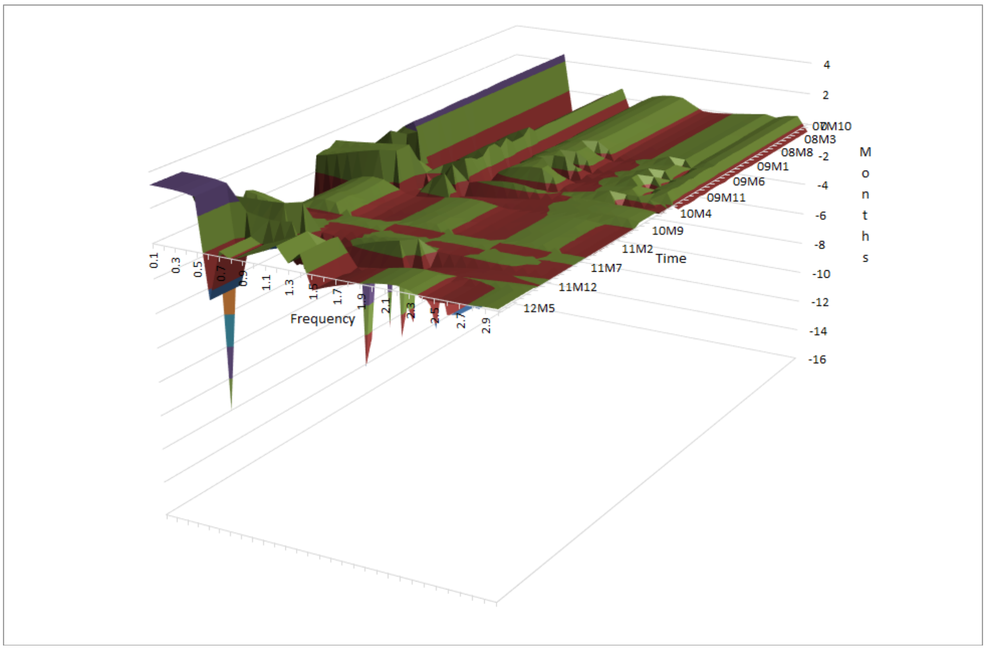

Figure 12. *Phase Shift CDS spreads – Unemployment Rate*

5. Conclusion

In this paper we investigated different determinants of the credit default swap. We did this by taking into account that a financial crisis may lead to structural changes so that an estimation technique is needed that is capable of catching them. For this reason we estimated the individual relationships using a state space approach.

What is also new is that we investigated the predictability of the CDS spreads in the frequency domain. As it turned out, some variables are able to predict the CDS spreads in the short run (inflation rate, SPX) whilst others are more reliable in the long run (deficit to GDP ratio).

Moreover, we could also demonstrate that the lead-lag relationship is, in most cases, not constant. In most cases, the Greek financial crisis altered this relationship. Sometimes the change was so drastic that this may be exploited as a warning signal for a crisis to come, even if the variable in question is not leading the CDS spreads. If one observes such changes in (for example) GFCF, GDP, capital utilisation or the current account balance, it may simply confirm that a crisis is imminent.

The case of US T-Bills is special, as the crisis clearly hinted a decoupling of the Greek financial crisis from the rest of the international capital markets. Whilst before the crisis, the CDS spreads were either leading the US T-Bills or was in phase with them, the CDS spreads lost the leading function for some frequencies in the crisis, which may be exploited as a warning signal for an imminent crisis.

An interesting case was capital utilisation where prior to the crisis the lead was only two weeks, but increased to up to six months during the crisis. The increase of the lead may serve as an important indicator for identifying a crisis.

Overall, there is no single variable that serves "best" as an indicator. In order to evaluate whether a crisis is looming a set of variables and how they change their lead-lag relationship should be considered.

Notes

[i] Grossman & Hansen (2010) point out that CDS pricing can be driven by a number of other factors not related with the issuer's creditworthiness such as the leverage underlying CDS trading, liquidity conditions, counter-party risk, and the general risk aversion of market participants. As these authors point out, understanding the limitations of CDS spreads as indicators of credit default is important because: (1) risk managers might overpay for credit protection during market distress; (2) credit investors might not be adequately compensated during benign periods and might incur opportunity costs during market distress; (3) portfolio credit risk and economic capital models based on CDS-implied probabilities of default might lead to inaccurate credit default estimates.

[ii] Bayesian Model Averaging (BMA) is used when there is uncertainty about the "true" empirical model. BMA relies on the concept of probability as a measure of the state of knowledge and provides more robust results than classical linear models with respect to the significance of the model's drivers.

[iii] As Barbosa & Costa (2010) point outglobal risk premium is influenced by the level of risk aversion of investors and by the degree of uncertainty prevailing in international financial markets.

[iv] Mody (2009), Sgherri & Zoli (2009), Barrios, Lewandowska, & Selzer (2009) and Schuknecht, Von Hahen, & Wolswijk (2010) focus on sovereign yield spreads on euro area countries and conclude that after the financial crisis, country credit risk seems to play a major role on determining the changes in sovereign credit spreads. Sgherri & Zoli (2009) measure country credit risk as market projected changes on country's debt. These authors conclude that, after the financial crisis, global risk conditions together with the market perception of country credit risk are the major drivers of the evolution on euro area sovereign yield spreads. This seems to suggest that markets impose more fiscal discipline after the financial crisis than in the early days of the common currency. Moreover, liquidity of sovereign bond markets appears to remain a relevant factor in explaining spread behaviour.

[v] See e.g. DeLong, Shleifer, Summers, & Waldmann (1990; 1991) for evidence that when irrational investors foolishly adopt aggressive trading they may earn higher return for bearing higher risk or for exploring information signals more aggressively (Hirshleifer & Luo, 2001). Also, irrational investors may gain from intimidating competinginformed traders (Kyle & Wang, 1997). Shleifer & Vishny (1997) and Xiong (2001) further suggest that a wealth transfer from rational to irrational investors tend to be magnified when mispricing becomes more severe which contributes for the self-feeding bubbles.

[vi] Second-generation models attempt to overcome the pitfalls of traditional models by considering not only economic fundamentals but also investor's beliefs as driving factors to explain the sudden occurrence of a crisis. Examples of other works relying on second-generation models are Eichengreen & Wyplosz (1993), Krugman (1996), Flood & Marion (1996; 1999).

[vii] Obviously, using the entire sample implies that we neglect possible structural breaks. The initial estimates may be biased therefore. The Kalman filter will then correct for this since, as Wells (1996) points out, the Kalman filter will converge to the true parameter value independently of the initial value. But choosing initial values which are already "close" to the true value accelerates convergence. Hence we employ an OLS estimate to start. But our start values have no effect on the parameter estimates by the time we get to 2012. Our results are robust.

[viii] Note that all our tests of significance, and significant differences in parameters, are being conducted in the time domain, *before* transferring to the frequency domain, because no statistical tests exist for calculated spectra (the transformations may be nonlinear and involve complex arithmetic). Stability tests are important here because our spectra could be sensitive to changes in the underlying parameters. But with the stability and specification tests conducted, we know there is no reason to switch to another model that fails to pass those tests.

[ix] The fluctuations test works as follows: one parameter value is taken as the reference value, e.g. the last value of the sample. All other observations are now tested whether they significantly differ from that value. In order to do so, Ploberger et al. (1989) have provided critical values which we have used in the figures (horizontal line). If the test value is above the critical value then we have a structural break, i.e. the parameter value differs significantly from the reference value and vice versa.

Appendix 1. Table of independent variables

INDEPENDENT VARIABLES	EXPECTED COEFFICIENT SIGN	DESCRIPTION/RELEVANCE
Deficit to GDP ratio	(+)	Negative ratio is likely to lead to a higher market perception of default risk and therefore a widening of credit spreads. Country deficits tend to point to problems in financing the government's budget by taxes which might be linked to a weak tax system or a weak state of the economy.
Total Government Debt to GDP ratio	(+)	Higher indebteness is likely to increase the default risk which tends to widener of CDS spreads. Higher indebtness means that the country's ability and willingness to pay back debt is weakened and thus a default is more likely.
GDP growth rate	(-)	If GDP growth is relatively high, the burden of debt to the economy tends to be not problematic. Therefore, CDS spreads are expended to narrow with the increase of the GDP growth rate.
Current account	(-)/(+)	This variable is an indicators of the international competitiveness of the economy. The higher the current account surplus, the higher the ability of the country to collect funds for debt servicing and the lower the market perception of default risk. In this context, the narrower the CDS spreads are likely to be. This scenario is related with Solvency (long term)arguments. Nevertheless, a current balance surplus mirrors a capital account deficit and this might indicate a country's inablity to borrow abroad or a foreign capital flight. To this extent, a increase on current account surplus might indicate a weakening of the country's ability to payback debt and thus a widening of CDS spreads. This scenario is related withLiquidity (short term) Arguments.
Inflation rate	(+)	Higher inflation rates (increasing price differentials) lead to a loss in competitiveness which increase the default risk. Thus, inflation rates are expected to be positively correlated with CDS spreads.
Gross Fixed Capital Formation (GFCF)	(-)	Higher capital formation is related to higher productivity and economic growth in the future. Therefore, higher capital formation is expected to lead to a higher future ability to service debt and to a lower spread in CDS.
Capital utilisation	(+)	An increase in capital utilisation might indicate a problem in terms of future economic growth and difficulties in future ability to repay the debt. Therefore, higher capital utilisation is expected to lead to a widening of CDS spreads.
Economic Sentiment Indicator	(-)	ESI reflects the expectation about the behaviour of the GDP in the near future. The higher the ESI the higher the investors confidence on the ability of the country to service its debt. Thus, higher ESI should lead to a lower spread in CDS.
Unemployment rate	(+)	An increase in unemployment rate can indicate a problem in terms of future economic growth. Therefore, the higher the unemployment rate the wider is likely to be the spread in CDS.
Global conditions		
US T-Bills interest rate	(-)	US T-bills represents a safe haven for investors is there a decrease of confidence in global capital markets. Therefore, a decrease in US T-Bills interest rate is likely to be related with a widening of CDS spreads.
S&P 500 Index	(+)	This variable reflects market participants confidence in the global economy and their willingness to invest in risky securities. Higher S&P 500 index is assumed to lead to higher CDS spreads.

Appendix 2: Regression Results

Table 1. *Regression Result CDS-GCFC*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.993543		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	8186.247161
Standard Error of Estimate	16888.19		
Akaike Information Criterion:	8.73E-06	Ljung-Box Test: Q*(16) =	24.89
Variable	Coeff	Std Error	T-Stat
Constant	-204.561	0.000101837	-2008714
CDS{1}	0.124007	0.106256049	1.1671
CDS{2}	0.854673	0.225962972	3.78236
CDS{3}	0.053307	0.058994856	0.904
CDS{4}	-0.55395	0.351967457	-1.57386
CDS{5}	0.156852	0.031161545	5.0335
CDS{6}	0.820503	0.304406611	2.695416
CDS{7}	-0.7564	0.380340204	-1.98874
GRGCFC	0.806136	0.131333266	6.138092
GRGCFC{1}	-0.07395	0.016704672	-4.42682
GRGCFC{2}	0.967648	0.202238742	4.784681

Table 2. *Regression Results for CDS - Current Account*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.986657		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	8186.247161
Standard Error of Estimate	1185.585		
Akaike Information Criterion:	3.57E-07	Ljung-Box Test: Q*(16) =	14.39
Variable	Coeff	Std Error	T-Stat
Constant	-0.06381	0.045365	-1.40657
CDS{1}	1.43128	0.395389	3.619935
CDS{2}	0.08368	0.060314	1.387376
CDS{3}	0.28228	0.177586	1.589568
CDS{4}	0.08678	0.090707	0.956712
CDS{5}	0.26461	0.061658	4.291517
CDS{6}	0.01503	0.167905	0.089513
CURR{2}	-0.01342	0.005379	-2.49562
CURR{7}	-0.17445	0.118631	-1.47052

Table 3. *Regression Results CDS – Deficit to GDP Ratio*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.986222		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	8186.247161
Standard Error of Estimate	1214.145		
Akaike Information Criterion:	0.0017	Ljung-Box Test: Q*(16) =	14.71
Variable	Coeff	Std Error	T-Stat
Constant	442.6658	262.038	1.689319
CDS{1}	0.45437	0.068729	6.611051
CDS{2}	0.19967	0.099139	2.013986
CDS{3}	0.34582	0.168805	2.048608
CDS{4}	2.17606	0.964819	2.255409
CDS{6}	-0.10904	0.609633	-0.17886
DEFGDPGR{1}	3.61903	1.967565	1.839347
DEFGDPGR{5}	-0.35503	2.039287	-0.1741
DEFGDPGR{6}	0.39882	0.120677	3.304863

Table 4. *Regression Results CDS – Annualised GDP Growth Rate*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.987435		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	8186.247161
Standard Error of Estimate	659.6086		
Akaike Information Criterion:	5.37E-10	Ljung-Box Test: Q*(16) =	23.265
Variable	Coeff	Std Error	T-Stat
Constant	1.05732	2.96E-06	357424.3
CDS{1}	0.39057	0.127557	3.06193
CDS{3}	0.26264	0.041555	6.32037
CDS{4}	-0.11373	0.043786	-2.5973
CDS{5}	1.46528	0.274428	5.33941
CDS{6}	-0.10522	0.096667	-1.0885
GDPANN{1}	-0.00004	0.004546	-0.00977
GDPANN{2}	0.01837	0.00486	3.780709
GDPANN{4}	0.02307	0.006032	3.824323
GDPANN{5}	0.02289	0.006692	3.421128

Table 5. *Regression Results CDS – Capital Utilisation*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.991212		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	8186.247161
Standard Error of Estimate	2695.314		
Akaike Information Criterion:	9.66E-05	Ljung-Box Test: Q*(16) =	23.587
Variable	Coeff	Std Error	T-Stat
Constant	149.4351	58.27108	2.564482
CDS{1}	-0.13586	0.754344	-0.1801
CDS{2}	0.48032	0.330746	1.45222
CDS{3}	0.74378	0.483855	1.537191
CDS{4}	0.4087	0.031565	12.94817
CDS{5}	0.18671	0.095099	1.963364
CDS{6}	-0.12933	0.382296	-0.3383
CAPUTILGR{4}	-0.09998	0.048424	-2.0647

Table 6. *Regression Results CDS – Inflation Rate*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.991004		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	8186.247161
Standard Error of Estimate	782.8037		
Akaike Information Criterion:	1.65E-05	Ljung-Box Test: Q*(16) =	24.016
Variable	Coeff	Std Error	T-Stat
Constant	196.5756	18.39033	2.471425
CDS{1}	0.738181	0.416695	-0.41693
CDS{2}	0.626831	0.425643	0.377229
CDS{3}	1.447387	0.473401	1.794659
CDS{4}	-3.25047	0.455001	0.266426
CDS{5}	3.376004	0.514208	3.012153
CDS{6}	-2.17971	1.354761	-0.28213
INFL{2}	-104.795	0.011345	3.125042
INFL{4}	-142.137	0.102642	2.273082

Table 7. *Regression Results CDS – Debt to GDP Ratio*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.981588		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	2255.83
Standard Error of Estimate	782.8037		
Akaike Information Criterion:	2.91E-06	Ljung-Box Test: Q*(16) =	26.122
Variable	Coeff	Std Error	T-Stat
Constant	7.243621	0.018312	395.5741
CDS{1}	0.119311	0.2698	0.44222
CDS{3}	0.464233	0.208792	2.223425
CDS{5}	6.192593	2.765185	2.239486
DEBTGDP{1}	0.504498	0.023114	21.82638
DEBTGDP{4}	-3.54005	0.235634	-15.0235
DEBTGDP{5}	-0.67689	0.022452	-30.1483

Table 8. *Regression Results CDS – Economic Sentiment Indicator*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.992328		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	2255.83
Standard Error of Estimate	1994.791		
Akaike Information Criterion:	1.30E-04	Ljung-Box Test: Q*(16) =	21.484
Variable	Coeff	Std Error	T-Stat
Constant	616.6602	292.7113	2.106718
CDS{1}	0.45962	0.049413	9.301705
CDS{2}	0.0991	0.017172	5.770707
CDS{3}	-0.04618	0.114419	-0.40362
CDS{4}	-0.29196	0.383226	-0.76185
CDS{5}	1.50927	0.514332	2.934425
CDS{6}	0.81033	1.654477	0.489778
SENTHAT	-4.25407	1.817214	-2.34099
SENTHAT{2}	-0.27798	0.295607	-0.94039
SENTHAT{5}	-0.19541	0.372092	-0.52517
SENTHAT{6}	-2.41441	1.147366	-2.10431

Table 9. *Regression Results CDS – SPX*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.991142		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	2255.83
Standard Error of Estimate	2212.844		
Akaike Information Criterion:	8.14E-05	Ljung-Box Test: Q*(16) =	15.628
Variable	Coeff	Std Error	T-Stat
Constant	5.04266	0.95454	5.282818
CDS{1}	-0.09157	0.554478	-0.16515
CDS{2}	0.462745	0.501669	0.92241
CDS{3}	0.858034	0.825902	1.038905
CDS{4}	0.350815	0.781032	0.449168
CDS{5}	-0.2899	0.025256	-11.4782
CDS{6}	0.353044	0.821537	0.429735
SPX	1.530998	0.623053	2.457252
SPX{3}	6.009305	2.860373	2.100882

Table 10. *Regression Results CDS – US T-Bills*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.990932		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	8186.247161
Standard Error of Estimate	2324.255		
Akaike Information Criterion:	2.45E-05	Ljung-Box Test: Q*(16) =	24.11
Variable	Coeff	Std Error	T-Stat
Constant	-1.63228	0.078394	-20.8215
CDS{1}	0.003747	0.316097	0.011854
CDS{2}	0.275511	0.450918	0.611002
CDS{3}	0.890714	0.519268	1.715325
CDS{4}	0.258084	0.649117	0.397593
CDS{5}	0.161275	0.036452	4.42434
CDS{6}	0.078314	0.967056	0.080982
CDS{7}	0.123744	1.518595	0.081486
TBILLUS{1}	1.253472	0.1664	7.532878
TBILLUS{2}	0.749977	0.572871	1.309156
TBILLUS{7}	1.75588	1.575972	1.114157

Table 11. *Regression Result CDS – Unemployment Rate*

VAR/System - Estimation by Kalman Filter			
Dependent Variable	CDS	Monthly Data From	2005:01 To 2012:06
Usable Observations	63		
Uncentered R^2	0.980991		
Mean of Dependent Variable	2976.072	Std Error of Dependent Variable	8186.247161
Standard Error of Estimate	3302.579		
Akaike Information Criterion:	0.00906	Ljung-Box Test: Q*(16) =	24.11
Variable	Coeff	Std Error	T-Stat
Constant	3351.886	908.2007	3.690689
CDS{1}	0.45963	0.132469	3.469725
CDS{3}	0.63102	0.370081	1.705096
CDS{4}	-0.04365	0.442439	-0.09866
UER	0.38066	0.388648	0.979455
UER{2}	3.14615	0.914122	3.441717
UER{3}	1.20722	0.446829	2.70176
UER{7}	1.25849	0.511012	2.46274

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