Modeling Credit Spreads:
An Application to the Sterling Eurobond Market.

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Abstract

This paper can be considered as a new perspective to analyse credit spreads. We follow a time series approach revealing the forces driving credit spread changes and volatility. Specifically, we aim to identify the process that describes the dynamic evolution of credit spreads on the Sterling Eurobond Index in the period 1991 – 1999. The time-series properties of credit spreads provide strong evidence of nonlinearities and high levels of intertemporal dependence in the credit spreads generating process. We introduce time-varying volatility models to capture the persistence in the conditional variance of credit spreads. To our knowledge Autoregressive Conditional Heteroskedastic models (ARCH and GARCH) have never been applied to credit spreads.

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1. Introduction

Financial institutions around the world are investing heavily in systems for measuring market and credit risks, responding to the request of better information by regulators and investors on one side, and to the internal risk monitoring needed by senior executives on the other side. The need for a deep understanding of credit risk is growing and will be further stimulated by several trends -financial market integration, privatisation, and disintermediation. Credit analysis is also likely to become more complex as new and innovative types of securities are being continuously created by financial engineering.

As debt markets grow more complex, they are also becoming more volatile. In an environment of increasing economic volatility, the task of forecasting credit risk is becoming more central to investment decisions and more resources will have to be committed to credit analysis. Investors will require access to timely and adequate information regarding the true nature of the credit risk to which they are exposed. This will enable them to take advantage of new opportunities, compare relative risks across new ranges of debt instruments and cross-border debt issuers, maximise yields and diversify investment risk. In brief, a better understanding of credit risk will contribute to stabilise the access to capital markets by helping both issuers and investors.

The traditional credit risk analysis, mainly a "straight ratios-based" analysis, is unlikely to be the answer to the current urgent needs. This type of approach was indeed appropriate when interest rates were stable and investors bought bonds to hold them to maturity. Bonds are nowadays traded with the purpose of making profits on interest rates movements or changes in the absolute or relative credit quality of the issuer. In this new environment a new modern approach is taking place, focusing on changes in the perceived credit risk.

Changes in the credit quality of a firm have been estimated inspecting the counterpart's financial statements, or analysing financial history, historical default rates and rating migrations from similar credit risk. However, financial statements are reports of the past and are therefore inherently backward looking. Moreover, traditional methods of adjusting exposure levels would entail participation in the secondary loan market and boosting credit-asset origination efforts in the relevant markets. Nevertheless, the illiquidity of the loan market, the possibility of damaging the relationship with the client, and the difficulty to originate assets in non-traditional markets, may all in fact make difficult the application of the traditional approaches.

The need to find viable alternatives to old mechanisms for adjusting credit-risk profiles have lead to adapting to credit risk variants of theories and methodologies previously used to address other financial risks. According to this new approach, changes in the market's expectations of default are directly recovered from the observation of price changes or credit spread changes. Alike in previous credit-risk management methodologies, looking at prices or yields that, by their nature, are inherently forward looking, will involve a more quantitative analysis of credit quality characteristics. In particular, credit risk can be measured as the fraction of price volatility that is related to the issuer itself and that differentiates from the price volatility generated by general market movements, namely market (general) risk. Alternatively, credit risk can be measured by credit spreads, which, theoretically, are attributable entirely to the corporation's default option.

This paper can be considered as a new perspective to analyse credit spreads. Within the credit spreads literature works have so far focused on three main areas: cross-sectional explanation of credit spreads and yield changes, specification of the risk structure of credit spreads, and valuation of risky debt. By contrast, we will follow a time series approach. In fact little is known about the forces driving credit spread changes and volatility. Moreover, we think that the identification of a process that describes the dynamic evolution of credit spreads is of great interest both to practitioners and academicians and needs to be explored more deeply. Specifically, we apply our analysis to the sterling Eurobond market and in particular we intend to identify what macroeconomic and financial factors have driven changes in the sterling Eurobond credit spreads in the period from January 1991 through May 1999. To our knowledge this is the first study of its kind on the Eurobond market.

One way of posing this issue will be to ask whether changes in credit spreads reflect economic fundamentals, or whether they represent a self-generated force bearing little relation to fundamentals. Credit spreads, like default rates, have shown to be not constant over time and there is general agreement on the direct impact that the state of the economy has on them. A report by Standard and Poor's (1997) states that "*A healthy economy in 1996 contributed to a significant decline in the total number of corporate defaults. Compared to 1995, defaults were reduced by one-half…*". Another report by Moody's

Investors Service (1996) argues that "*The sources of [default rate volatility] are many, but macroeconomic trends are certainly the most influencial factors*". We, therefore, expect credit spreads to adjust as general macroeconomic and regulatory variables, business environment, conditions in firms' factor, and output markets unexpectedly change altering firms' credit outlooks.

The remainder of the paper is structured as follows. Section 2 presents an overview of the literature of credit spreads. Section 3 describes the data and extensively presents the time series properties of credit spreads. An appropriate model to explain the behaviour of changes in credit spreads is derived and estimated in Section 4. Section 5 summarises and concludes the main findings of the paper.

2. Literature Review

As mentioned in the previous section, the main studies and key findings related directly or indirectly to credit spreads have so far focused on three main areas: a) explanation of credit spreads; b) specification of the risk structure of credit spreads; c) valuation of risky debt.

Most works focused on the determinants of bond yields and yield premia -obtained by subtracting from the corporate bond yield the yield observed on a risk-less security of the same maturity- use cross-section regression analysis to determine the variables significant in explaining credit risk premia. The most common factors are: i) proxies for the default risk -earnings variability, time of no default, market equity value over par value of debt- (Fisher, 1959; Boardman and McEnally, 1981; Nielsen et al.1993; El-Jahel, 1998); ii) supply and demand factors (Fair and Malkiel, 1971); iii) bond specific features -callability, marketability, coupon rate, sinking fund, security status, recovery factor, industrial classification- (Fisher, 1959; Silvers, 1973; Duffee, 1998; Boardman and McEnally, 1981); iv) actual default rates (Fons, 1987); v) returns on the firm's assets (Longstaff and Schwartz, 1995); vi) firm's capital structure (Leland, 1994); vii) business cycle and confidence variables –consumer sentiment, returns on stock indices, industrial production, inflation, unemployment- (Jaffee, 1975; Longstaff and Schwartz, 1995; Fons, 1987) and viii) interest rate variables –short- and long-term rate, term spread, interest rate volatility and expectations- (Mella-Barral and Tychon, 1996; Fons, 1994; Kim et al., 1995; Duffee, 1998). Another large part of the literature deals with the term structure of credit spreads. The idea underlying the risk structure of credit quality is that spreads on corporate bonds vary with maturity, *ceteris paribus*. The idea reflects factors such as the crisis at maturity and the pattern of marginal default risk. The crisis at maturity hypothesis assumes that highly leveraged firms with debt maturing over the near term may encounter refinancing problems, which is reflected in higher spreads at shorter maturities. The marginal default risk is observed to increase with maturity for higher rated firms and decrease with maturity for lower rated firms (Fons, 1994). This pattern is consistent with two strongly linked observed phenomena: the mean-reverting process in credit quality and the life cycle of ratings outlook. Most theoretical and empirical works infer that high quality firms are unlike to default in the short term. Over the longer term, however, they may experience credit quality deterioration or ultimately default. Middle-rated firms tend to maintain their rating, and lower quality firms while facing immediate prospect of default, they are likely to overcome their state of financial distress in the long period. From the credit quality mean-reverting feature the life cycle of ratings outlook can be inferred and explained in terms of different shapes of the term structure of credit spreads. Specifically, the term structure of credit risk is upward-sloping for highly rated bonds, hump-shaped for middle-rated firms, and strictly declining for low-rated firms (Johnson, 1967; Merton, 1974; Kim et al., 1995; Sarig and Warga, 1989; Jarrow, Lando and Turnbull, 1997). Nielsen et al. (1993) and El-Jahel (1998) extend previous works showing how the term structure of credit risk is highly sensitive to changes in the volatility of the firm's assets. Mella-Barral and Tychon (1996) illustrate how differences in the parameterisation of the event of default affect not only bond valuation, but also the implied term structure of credit spreads. Helwege and Turner's (1999) investigation provides some empirical support for the practitioners' view of an upward-sloping credit yield curve for most speculative-grade firms.

The last approach of the literature concerns the valuation of risky debt. The basic idea underlying risky bond pricing models is that the inherent credit risk of any credit transaction should be compensated by a return (calculated as the spread received) commensurate with the risk of default (both on expected and unexpected losses), the credit exposure, and the recovery rate in the event of default. Models for valuing defaultable bonds have developed and significant progress has been made in modeling credit risk since the pioneering work of Black and Scholes (1973) and Merton (1974), both based on option theory. A number of papers (*proprietary models*) have used and extended the option-based approach and removed in turn some of its strong assumptions. Geske (1977) extends the analysis to risky coupon bonds that have a finite time to maturity and discrete coupon payments. Black and

Cox (1976) extend Merton (1974) to the study of safety covenants, subordination arrangements, and limits on the financing. Brennan and Schwartz (1977) model convertible debt with stochastic interest rates. Mason and Bhattacharya (1981) study the firm value as a discontinuos process and with complex boundary conditions. Turnbull (1979) extends the Merton's model to an economy with both corporate tax and bankruptcy costs. On the same line is the work by Leland (1994) which involves notions of optimal capital structure. Cooper and Mello (1991) and Rendleman (1993) apply Merton's model to the valuation and analysis of risk sharing in swaps with default risk.

The subsequent literature on defaultable bond pricing has taken two approaches: the structural approach and the reduced form approach. *Structural models* (or models based on the value of the firm) specify a particular firm value process and assume that default is triggered when firm value hits some specific threshold. The latter is typically a function of the amount of bond outstanding. In these models bankruptcy is allowed to occur at a random time and the causality of default is directly linked to information on the asset of the firm –the total value of the firm's assets is employed as the economic fundamental. This approach is used in Hull and White (1995), Longstaff and Schwartz (1995), Kim, Ramaswamy and Sundaresan (1992) and Nielsen, Saa'-Raquejo, and Santa-Clara (1993).
In *reduced form models* or intensity based models, alike in structural models, the default process is directly specified and is represented by a Poisson or "jump" process –to describe the idea that the timing of default takes the bond-holders by surprise- not explicitly depending on the firm's underlying assets. The default event is not defined and occurs at a random time and an exogenous and somewhat arbitrary recovery rate is assumed. The simplest model is presented in Jarrow and Turnbull (1995) where the recovery rate is constant, the default process is modeled as a jump process, and the default time is exponentially distributed. Jarrow, Lando and Turnbull (1997) model default time as the first time a continuous time Markov chain hits the absorbing state represented by the default event. An application of the Markov model, modified to have random recovery rates, can be found in Das and Tufano (1995). Lando (1995) describes default as the first jump time of a Cox process which can be thought of as a Poisson process with a random intensity. Another early use of stochastic intensity is in Madan and Unal (1995) where the intensity is modeled as a function of the excess return on the issuer's equity, and the recovery rate is specified as a random variable independent of the recovery rate process. Although this class of models is

widely used in practice because of its analytical tractability, the abstraction from the underlying firm value makes it less useful for suggesting determinants of credit spreads.

It should be noted that the distinction between the structural approach and the reduced form approach is not clear-cut. Models which use the value of the firm could easily be intensity based by describing the value of the firm as a jump process, and intensity based models could easily incorporate the value of the firm by using it as a variable affecting the default intensity. A summary review of the default risk literature is contained in Sundaresan (2000), where the various models are compared and their impact in the industry discussed.

Alongside the literature on corporate credit spreads a number of papers have focused on government and emerging market credit spreads. As it is beyond the scope of this paper to analyse directly the empirical evidence on credit spreads in these markets, we briefly present the main line of research in this area. Globalisation, country performance variables (GDP growth, per capita income, inflation, external and internal balance, etc.), currency denomination, rating, default history, and maturity have been the explanatory variables generally investigated to explain sovereign spread changes. However, the role of industrial countries short-term interest rates and its linkage with government spreads has received most of the attention. The presence of a positive relationship between interest rates and credit spreads is generally explained either in terms of a creditworthiness effect or through an "appetite for risk" hypothesis. Kamin and von Kleist (1999) find little evidence of a short-term relationship between industrial country interest rates and emerging market bond spreads. This result confirms findings in previous works: both the long-term US Treasury bond interest rate (Cline and Barnes, 1997) and the short-term US Treasury bill rate (Min, 1998) are found to be positively but not significantly related to credit spreads on new bond issues.

Much work has been done in the credit risk field, but considerable challenges remain. The numerical implementation of the models described above often requires unsatisfactory assumptions on the independence between the risk-free interest rate and the process driving default. Another concern is the inability of the models to explain the time-series behaviour of credit spreads and the relative level of spreads in different parts of the market (Cooper and Mello, 1988). Moreover, most of these models cannot generate sufficient time-series variability in the spreads to match actual rates. Concluding, the behaviour of actual spreads is very complex and, as yet, no model adequately captures this complexity (Brown et al. 1994). Unless a model can do this, it will not be useful in determining the relative prices of new credit derivatives, some of which are so extremely sensitive to the time-series properties of the spreads.

3. Time series properties of credit spreads

3.1. The Data

We focus on the Eurobond market, which, we believe, has not received by the academic finance literature the attention commensurate with its size and importance. In particular, we model credit spreads on the ISMA sterling Eurobond index[1], which is a market-value weighted, redemption yield index of straight Eurobonds, calculated by ISMA Ltd, London, from December 30, 1990, and made available on a daily basis through Datastream International. The daily data set extends from December 30, 1990 to May 26, 1999 for a number of 2193 observations and includes such extreme events as the European exchange rate mechanism crisis of 1992.

ISMA indices are provided for three different life-to-maturity bands: over 1 year –i.e. all maturities-, 1 to 5 years and over 5 years. We decided to use the index associated to the larger maturity band. The rationale underlying our choice was to match as much as possible the maturity of the Eurobond index with the maturity of the UK-government bond index that we used as a benchmark. Both indices are indeed characterised by an average life to maturity of 10 years.

Table 1 shows the general composition of the ISMA Eurobond index. Eurobonds included in the index and issued in the period 1991-1999 have been classified according to the country (or origin) of the issuer, the issuer credit rating, and the issue credit quality. Over the 8-year period, on average 69 percent of the total volume of new issued and outstanding Eurobonds was from UK, 16 percent from a European country, 6 percent from USA,

[1] The bonds used in calculating the index are selected once a month for inclusion throughout the following month. The universe of bonds from which the selection is made consists of those bonds for which ISMA has adequate prices on the last Friday of the month. An adequate price is a price averaged from a minimum number of market makers with a maximum price spread. Bonds must be fixed rate "bullet" bonds. That is, they must not have a sinking fund or a call or a put option. Bonds will be rejected if: i) they have special features, for example dual currency options and index linking; ii) they are partly paid, in default; iii) they have a maturity yield vastly different from other bonds in the same category; iv) they are new issues, and the closing date is after the end of the month; v) they are fungible into another bond before the end of the next month; vi) zero coupon bonds are also rejected because they yield less than conventional bonds of similar duration.

Canada and Latin America, and 5 percent from Japan, Asia and Oceania. The share of UK borrowers in total issuance has fallen over time, while European and USA borrowers have increased their participation in the Eurobond market. As far as the maturity structure of the Eurobonds is concerned, 32 percent are characterised by a life to maturity between 7 and 10 years, 26 percent between 3 and 7 years, and 20 percent between 20 and 30 years. Most important is the average credit rating of the index. Specifically, AAA- and AA-rated bonds constitute on average 40 and 42 percent, respectively, of the total market value of the issues. The stake of most creditworth borrowers (AAA) has not shown any trend over the period, while AA-rated bonds are characterised by a decreasing trend alongside with an increasing trend for the A-rated bond fraction. As we expected the quality of the bonds in the sample is generally high. The investment-grade bias reflects the fact that issuers traditionally need to be a high credit standing to be able to raise capital in the Eurobond market, together with a regulatory bias (Dale and Thomas, 1991). Our analysis will benefit from this feature in the sense that yields on investment-grade bonds will have relatively more of their volatility attributable to credit spread movements than sub-investment grade credits, which will be primarily driven by potential company-specific default events.

Credit spreads (CS) are defined as the continuously compounded yield differencial between the ISMA index and the UK long-term (10 year) government bond index. The latter is provided by Datastream too[2]. From Favero et al. (1996) we know that the simple difference between rates (discrete time compounding) is affected by the *level* of the reference rate. This argument might be termed as the "mathematical" effect and in our case it implies that credit spreads would be an increasing function of the level of the benchmark index yield. In the simplest case of two one-period interest rates, r^{EB} and r^{TB}, which are the rate on a risky instrument (with probability of being repaid $p<1$) and the rate on a safe instrument, respectively, in equilibrium the following equality holds:

$$(1+r^{TB}) = p(1+r^{EB}) + (1-p)0, \tag{1}$$

from which we can derive the formula for the spread as

[2] The Datastream codes for the ISMA index and for the Benchmark index are respectively: ISMSTG5(RY) and BMUK10Y(RY). The datatype RY stands for gross redemption yield and is a good approximation to the average yield of a portfolio. The RY of the index is obtained by weighting the individual bond yields by the size of the holding multiplied by the duration.

$$1\text{-}r^{TB} = (1+r^{EB})(1\text{-}p)/p. \tag{2}$$

As long as p<1, increases in the risk-free interest rate lead to an increase in the amount that has to be repaid by the risky borrower. However, as it is not certain that the risky borrower will be able to repay its additional debt, the yield on the risky instrument must rise more than proportionately respect to the safe instrument. Hence an increase in the risk-free rate is likely to raise the spread only for "mathematical" reasons (Kamin and von Kleist, 1999).

To eliminate the effect of discrete time compounding, credit spreads are converted to become continuous compounding by the transformation:

$$cs_t = ln(1+r^{EB}) - ln(1+r^{TB}) \tag{3}$$

and changes in credit spreads at time *t* are defined as:

$$dcs_t = cs_t - cs_{t-1}, \tag{4}$$

with t = 1, 2, …, 2193 days.[3]

Note, however, that despite the fact that credit spreads are obtained by subtracting a risk-less rate of interest from a yield on a corporate bond, they are not a spread that is the result of the interaction between two assets. In fact, in the remainder of the paper credit spreads will be considered an independent financial asset.

3.2. Credit Spreads Stylised Facts

In this section we will look at the time series pattern of both credit spread levels and changes. Figure 1 plots credit spread levels over the entire sample period. We can recognise a rather cyclical behaviour of credit spreads over the period with a decreasing trend from the beginning of 1991 to the end of 1992. From 1997 the series appears to trend steeply upward until the end of 1998 and then stabilise around the same mean level it had experienced before 1992.

Figure 1 plots also credit spread changes over the same sample period and shows credit spread volatility fluctuations over time. Credit spread volatility appears high at the end of 1992 and in 1994, and very high from late 1998. In addition, from the plot of the absolute changes in credit spreads (Figure 1), it emerges that large absolute changes are more likely than small absolute changes to be followed by a large absolute change. The evidence of volatility clustering suggests that a suitable model for the data should capture this time varying volatility structure.

It is worth focusing for a while on the recent remarkable rise in volatility observed after May 1997, when the Thai baht was subject to severe speculative attacks and finally devaluated. The crisis subsequently spread to other emerging and developed markets. Until July 1998 – Russia's financial crisis- however, the mature financial markets in the United States and Europe were generally buoyant and little affected by the Asian crisis. However, the crisis in Russia sparked a broad-based reassessment and repricing of risk, especially regarding emerging market investments, and a large-scale of portfolio rebalancing across a range of global financial markets. We can therefore explain the reflection of the Asian crisis on the Eurobond market in terms of "contagion" effect. As the crisis was worsening, the global credit crunch caused by investors' loss of appetite for risk began to drive up the yield spreads in the whole fixed-income universe, apart from the treasury markets of the strongest economies. This is reflected in the huge credit spread widenings in the last two years mainly due to the large fall in the government bond yields rather than to a rise in actual borrowing costs.

Main descriptive statistics for the CS series are presented in Table 2. Credit spreads present positive skewness (sk = 2.035), and since price changes present skewness in the opposite direction than that of yield changes, positive credit spreads skewness implies that the left tail of the loss distribution (for a long position) contains more probability than a normal one. Credit spreads are also leptokurtic (k = 7.734) and therefore characterised by a fairly large likelihood of small credit spreads, coupled with a small chance of large credit spreads. This is in line with the specific feature of credit risk to be subject to small frequent variations and rare large variations. Table 2 reports also various descriptive statistics for the dCS series. The series while is roughly symmetrically distributed, it presents fat tails (k = 8.79).

[3] Note that the natural logarithm specification is generally preferred as it captures the nonlinear relationship between yields and ratings (Kan, 1998; Cantor and Packer, 1996; and Kamin and von Kleist, 1999).

Summarising, credit spread levels and changes present signs of the characteristic fat-tailed behaviour and in both cases the Jarque-Bera χ^2 statistic for the null hypothesis of normality is far beyond the critical value at the 1 percent level, which suggests that the two series are far from a normal distribution. The significant deviation from normality can be a symptom of dependence or nonlinear dynamics. Before going into any further discussion, we have first to identify the process generating credit spreads.

3.3. The Variables

As the risk of a change in credit quality varies over time, we collected a set of variables in order to test for their correlation and influence on the time series of Eurobonds credit spread levels and changes. Since the credit spreads we are using are computed on an index, we expect them to be affected mainly by financial and macroeconomic variables, rather than by firm-specific factors[4]. We present the variables below.

- R^{FTSE} and DY^{FTSE} are the return and the dividend yield series on the FTSE All Share index, respectively. The former is a proxy for the economic confidence and we would expect credit spreads to narrow as R^{FTSE} increases. The correlation of credit spreads to equity indices is consistent with the Black and Scholes model (Black and Scholes, 1973) of firm capital structure. The higher the leverage of the firm (large CS), the lower is the positive difference between the value of the firm and the value of the bonds, and in turn the lower correlated are changes in bond value and in the risk-free bond values. Moreover, while considering constant the firm's probability of default, changes in credit spreads may occur due to changes in the expected recovery rate. The expected recovery rate, in turn, is likely to be a function of the general business climate (Altman and Kishore, 1996). As a result, in a poor economic climate investors will move to a more conservative credit risk exposure (*flight to quality*), and credit spreads will widen. Following the same logic, we expect credit spreads to narrow in periods of boom. As far the DY^{FTSE} is concerned, we expect a positive relation with credit spreads. Increases in the dividend yield make indeed the equity market more as a yield-bearing investment.

- SHORT and LONG are the interest rate on the 3-month Treasury bill and the redemption yield on the UK government bond index with 15 years life to maturity, respectively. While the short-term interest rate should reflect the stance of monetary policy and hence the country (UK) liquidity, the long-term interest rate should capture the expectations of future UK inflation. If we consider a corporate bond as being equivalent to a portfolio composed of a risk-free asset and a short position in a put option on the value of the firm (Merton, 1974), a rise in the default-free rate of interest would reduce the value of the put option that bondholders have granted to shareholders. This, in turn, increases the value of corporate bonds and reduces their yield. Longstaff and Schwartz (1995) reach the same conclusion pointing out that the static effect of a higher spot rate is to increase the risk-neutral drift of the firm value process. A higher drift reduces the incidence of default, and in turn, reduces the credit spreads. From the demand and supply perspective, a decline in interest rates may cause the supply of corporate bonds to increase which lowers their price and hence raise their spreads. On the other hand, a positive relationship between interest rates and credit spreads may be explained in terms of a creditworthiness effect and through the "appetite for risk" hypothesis. According to this hypothesis, an increase in the interest rates increase the debt burden by borrowers, thereby reducing their ability to pay and lowering their creditworthiness. Moreover, in front of a general reduction in interest rates investors will enhance portfolio returns by increasing their risk exposure, the demand for corporate and higher yield bonds will raise and credit spreads in turn will narrow. The final and net impact of interest rate changes on spreads is therefore a matter of empirical evidence. A weak but significant negative relationship between changes in credit spreads and interest rates is found by Duffee (1998) on a sample of non-callable bonds. A negative short-term relationship is also found in Morris, Neal and Rolph (1998) and Bevan and Garzarelli (2000) who explain that in the short-term spreads narrow because a given rise in Treasuries produces a proportionally smaller rise in corporate rates. However, a cointegration analysis shows that over the long run this relation is reversed.

- TERM represents the term spread, calculated as the difference between the long-term interest rate and the three-month interest rate (LONG-SHORT). The slope of the Treasury yield curve is a proxy for the real interest rate risk. This measure has been used in many bond and interest rate studies (see Clare et al. 2000, Nelson and Schaefer, 1983). If the short rate dynamics depend upon the long rate (Brennan and Schwartz, 1979), we can here extend the logic of Longstaff and Schwartz (1995). If the short rate is expected to mean-revert to the long rate, then an increase in the slope of the Treasury curve should increase the expected future short rate, again leading to a decrease in credit spreads. From a different

[4] All the variables are available from Datastream International.

perspective, we would expect the flattening of the benchmark curve imply a weakening economy on one side and a steepening of generic and individual issuer yield curve on the other side. Moreover, the expected recovery rate might decrease in times of recessions and corporate investors presumably would demand a higher risk premium (more long spreads) to extend the maturity from 10 years to 30 years with a flatter underlying yield curve. All these factors therefore support a negative relationship between credit spreads and the slope of the Treasury yield curve.

- LT_DY is the bond and equity yield ratio. Specifically, it is the ratio of the yield on UK long-term government bonds to the dividend yield on the FTSE All Share index. This has been formalised for the UK equity market in a predictive time series sense by Clare, Thomas and Wichens (1994) and as a macroeconomic-financial source of risk priced in the UK equity market by Clare and Thomas (1994). From this perspective, the ratio can be interpreted as reflecting a substitution effect between the bond and the equity markets within the current economic-financial outlook. In an increasingly risky environment, we expect investors move from the equity to the gilt market, and for demand and offer laws bond prices will rise, lowering credit spreads. As a result a negative relationship is likely to be observed between the two variables.

- DOLLAR and MARC are the US dollar and German mark to UK sterling exchange rates, respectively. They are a measure of the relative strenght of the UK sterling and are expressed as US dollars or German marcs per unit of sterling. Since the bonds pay UK sterling, the stability of the exchange rate helps to support the sterling Eurobond market by limiting the currency risk faced by overseas borrowers. Moreover, in the event of an increasing strenght of the sterling, overseas issuers will face a higher price of their debt. This heavier debt burden might compromise their ability to repay the debt and their creditworthiness, raising the bond yields. We would therefore expect an increase in the exchange rate to lead to a widening of credit spreads. The existence of a relationship of this kind is supported by Clare et al. (2000), where a positive risk premium on Eurodollar bonds is found attached to the rate of change in the US effective exchange rate.

Descriptive statistics for the variables discussed above are presented in Table 2. We can generally see that most of the variables in differences present means not statistically different from zero, if the standard deviation could be used to produce *t*-ratios. However, despite low skeness values, the unconditional distributions of all series show high kurtosis, and are therefore nonnormal[5].

Table 3 presents the correlations between credit spreads and the financial variables presented above. Credit spreads are significantly and positively correlated with changes in credit spreads and with the exchange rate variables. The higher the exchange rate is, that is the stronger the sterling, the larger the credit spreads. Moreover, credit spreads are strongly negative correlated with the term spread and with the long-term rate, but positively correlated with the short-term interest rate level. Finally a negative correlation is measured against the dividend yield of the FTSE All Share Index; while credit spreads are positively correlated with the FTSE All Share Return index and the long-term interest rate to dividend yield on the FTSE All Share Return index ratio.

Table 3 presents also correlations for credit spread changes. We can see how changes in credit spreads are negatively correlated with changes in the interest rate variables –especially high is the correlation coefficient with changes in the term spread and in the long-term interest rate. Positive correlation is found with the return on the FTSE All Share index. Finally negative correlation is oberved with changes in the long rate/dividend yield ratio and with changes in the dividend yield of the FTSE All Share index.

3.4. Autocorrelation Structure

We proceed now to explore the time-series properties of credit spreads employing the Box and Jenkins (1976) methodology for appropriate model selection. As a first step of the identification stage we address to the question of dependence in credit spreads. Since a series cannot be independently distributed if any of its autocorrelation coefficients are non-zero, we compute the autocorrelation function (ACF) of the CS and dCS series followed by tests that the serial correlation coefficients are zero. The pattern of autocorrelations and partial autocorrelations (PACF) is also important in indicating the plausible structure and nonlinear dynamics of the CS process. In Panel A of Table 4 we present the sample autocorrelations from lag 1 to 5 and 10, 20, 40, 70 and 100 for CS, $|CS|$, and $(CS)^2$. In addition the autocorrelogram of CS, $|CS|$, and $(CS)^2$ from lag 1 to lag 100 is plotted in Figure 2 with the dotted lines representing the 95 percent confidence interval for the estimated sample autocorrelations if the CS process was independently and identically

[5] As a consequence the *t*-test cannot be conducted.

distributed (*i.i.d*.). The sample correlogram shows a smooth decay for the CS series, and the sample partial correlogram in Figure 3 shows two significant spikes in correspondence of the first two lags, suggesting a simple second-order autoregressive model. The first lag autocorrelation for CS is 0.988, which indicates the presence of a unit root for credit spreads.

Panel B in Table 3 exhibits the sample autocorrelations for dCS, $|\text{dCS}|$, and $(\text{dCS})^2$, and the autocorrelograms of dCS, $|\text{dCS}|$, and $(\text{dCS})^2$ are plotted in Figure 2. Firstly, we note that about one sixth of the sample autocorrelations within lag 100 are outside the 95 percent confidence interval. Secondly, if dCS was as an *i.i.d.* process then any transformation of it should also be an *i.i.d.* process. In other words, if the dCS series had a finite variance, then the standard error of the sample autocorrelations of $|\text{dCS}|$ would be still within the confidence interval and the same standard error would be applicable for the sample autocorrelations of $(\text{dCS})^2$, providing that CS has also finite kurtosis. From Figure 2 it emerges that not only most of the autocorrelations of $|\text{dCS}|$ and $(\text{dCS})^2$ are outside the confidence interval, but also that they are all positive, which suggests that dCS^2 series might be characterised by a long-term memory structure. In other words, the dependence between close observations may not necessarily be stronger that that one between distant observations, or the most recent market information may not necessarily be more useful than past information. In order to provide a more robust test for long term dependence in the daily credit spread changes, we used the R/S methodology that looks at the scaling behaviour of the rescaled cumulative deviations of dCS^2 from the mean. We estimated the Hurst exponent (Hurst, 1951), which is expected to be between 0.5 and 1 if the long memory structure exists. The sample period has been split into subsamples according to the pattern of the volatility as resulting form the CUSUM square test for variance stability (see Section 4.1). Specifically we have identified five subperiods as follows: 2 January 1991 to 15 October 1991 (205 obs), 16 October 1991 to 21 June 1994 (700 obs), 22 June 1994 to 25 April 1995 (220 obs), 26 April 1995 to 26 February 1999 (1003 obs), and 27 February 1999 to 26 June 1999 (63 obs). The Hurst coefficient (H) was computed for the whole sample period and for each subperiod (with their respective expected values in brackets). Results indicate significant positive long-term memory for the whole sample (H=0.85, R^2=0.99), the third (H=0.684, [0.587]), and marginally the second periods (H=0.576, [0.574]). The null hypothesis of no long-term dependence is strongly rejected for the first (H=0.578, [0.591]), fourth (H=0.551, [0.574] and fifth subperiods (H=0.573, [0.616]). In conclusion the evidence so far is not in favor of an *i.i.d.* process for the credit spread changes process.

Despite the strenght of the evidence in favor of long memory, this result may be due to the aggregation effect deriving from the use of a bond index. The key idea is that the aggregation of weakly dependent series can produce a strong dependent series (Lobato and Savin, 1996). This possibility could be examined at a later stage in two ways: analysing the long memory properties of a subsample of individual bonds included in the index, and applying the modified R/S analysis to produce a new R/S statistic (Lo, 1991) robust to short-term dependence, heterogeneities and nonstationarity.

From the observation of the correlogram for dCS it is clear that both the ACF and the PACF are zero after two lags. The negative sign of the first autocorrelation coefficient (=-0.32) suggests a mean-reverting behaviour of credit spreads. We presume an AR(2) specification is a parsimonious representation of the process governing the residuals and we consequently present in Panel C of Table 4 autocorrelations of the residuals, squared and absolute residuals of an AR(2) model for dCS:

$$Dcs_t = a + b_1 Dcs_{t-1} + b_2 Dcs_{t-2} + e_t \tag{5}$$

An AR(2) specification was selected as the best specification. Despite this specification was able to remove all serial correlation in the residuals up to lag 5, the correlograms of the absolute and squared residuals display a very similar pattern to their counterparts in the dCS series. The Box-Pierce Q statistics for all lags up to 100 are much higher than the critical values, rejecting the null hypothesis of zero autocorrelation. This implies that the residuals exhibit high levels of intertemporal dependence and suggests the need of a model able to capture all the stylised facts emerged so far: lack of independence, nonlinearities in the series, implied persistence in conditional variance and excess kurtosis.

3.5. Credit Spreads Stationarity

The second step towards the identification of the best model fitting the data consists in recording evidence about credit spreads intertemporal stationarity in order to avoid any potential spurious regression problem. The autocorrelation functions were examined and the Augmented Dickey-Fuller (ADF) test for the presence of a unit root was implemented to determine the integration order of the series. The ADF test was first applied to credit spread levels. Since, the CS series does not exhibit any trend and has a mean close to zero, neither a trend nor a constant were introduced in the test regression. Both Akaike and Schwarz's information criteria selected an autoregressive model of order (2). For the ADF test, the test statistic is the *t*-statistic for the lagged dependent variable in the test regression. As the *t*-statistic is 0.029 and lower (in absolute terms) than the 95 percent MacKinnon critical value (-1.93), the test fails to reject the null hypothesis of a unit root in the CS series at any significance level. The ADF test was successively applied to the first difference of the CS series and in this case the null hypothesis of non-stationarity could be rejected (*t*-statistic=-41.48, critical value=-1.93). The dCS series is found to be stationary at any significance level. In conclusion, the CS series is integrated of order 1, I(1).

As the ADF test assumes a moving average process for the error series (Said and Dickey, 1984), we implemented also the Phillips-Perron (1988) test, which is a semi-parametric (*Z*-statistic) method that allows for higher-order serial correlation and heteroskedasticity in a series. The P-P test results to be desiderable for its weaker set of assumptions concerning the error process and for its greater power to reject a false null hypothesis of a unit root.[6] The P-P *Z*-statistic is -0.018 and -67.43 for CS and dCS, respectively, and the critical value at the 95 percent level is still -1.93. The null hypothesis of a unit root is rejected only for the dCS series. The results obtained performing the P-P test are therefore totally consistent with those provided by the ADF test.

An alternative way to test for stationarity is to focus on the nature of the variance of the CS series, that is implementing the variance ratio test (Poterba and Summers, 1988). If the CS series is I(1) taking

$$D_k cs_t = cs_t - cs_{t-k}\,, \tag{6}$$

$$D_1 cs_t = cs_t - cs_{t-1}\,, \tag{7}$$

and the ratio

[6] The cost of weaker assumptions lies in the fact that in the presence of negative moving average terms, the P-P test tends to reject the null of a unit root whether or not the actual data-generating process contains a negative unit root. Hence, it is preferable to use the ADF test when the true model contains negative moving average terms and the Phillips-Perron test when the true model contains positive moving average terms.

$$\lambda = \frac{var\,\Delta_k cs_t}{var\,\Delta_1 cs_t}, \tag{8}$$

a plot of λ against k should be an increasing (straight) line. If CS does not have a unit root both Δ_kCS and Δ_1 CS will be constant, so that the ratio λ does not change after k becomes large enough. However, as Figure 4 shows, the variance ratio is increasing with k, suggesting the presence of a unit root and confirming the results from the ADF and P-P tests. The variance ratio test has also been applied to credit spread changes. The value of the ratio displays an oscillating behaviour around its mean value of 0.756 for any value of k (Figure 4), which is evidence of stationarity for the dCS series. According to Poterba and Summers (1988), the fact that the variance ratios lie below unity is also evidence of mean reversion.

3.6. Cointegration Analysis

The ADF test was also applied to all the macroeconomic and financial series in levels presented in Section 3.3 and all of them were found to be non-stationary and I(1). In this section we are interested in determining whether the CS series is cointegrated with any of the financial variables, and if it is, in identifying the cointegration or long-run equilibrium relationship. Two previous studies estimated the long-run relationship implied in the yield premium using cointegration analysis. A cointegrating vector was found between Treasury yields, noninvestment grade bond yields, and default rates by Barnhill, Joutz, and Maxwell (2000). Moreover, Morris, Neal and Rolph (1998) show that corporate rates are cointegrated with government rates and the relation between Treasury rates and credit spreads on Moody's seasoned bond indices is negative in the short-run and reverses to be positive in the long-run.

The Johansen’s cointegration methodology was employed as it has been proven to be more powerful respect to other alternative techniques (Gonzalo, 1994). Furthermore, the Johansen approach offers a test statistic for the number of cointegrating vectors and allows direct hypothesis tests of the coefficients entering the cointegrating vector.

The only variable that showed to be cointegrated with credit spreads is the FTSE All Share Price index. We now turn to see how the test develops. In the Johansen procedure, maximum likelihood is applied to an autoregressive representation of the form given by the following equation:

$$\begin{bmatrix} DCS_t \\ DP^{FTSE}{}_t \end{bmatrix} = G(L)\begin{bmatrix} DCS_{t-1} \\ DP^{FTSE}{}_{t-1} \end{bmatrix} + P\begin{bmatrix} CS_t \\ P^{FTSE}{}_t \end{bmatrix} + \begin{bmatrix} e_t^{CS} \\ e_t^{P^{FTSE}} \end{bmatrix} \tag{9}$$

where $\Gamma(L)$ is a 2×2 matrix of polynomials in the lag operator. The Johansen test is on the rank of the long-run impact matrix Π. In the absence of cointegration, Π is a singular matrix (rank = 0). Hence, in our case, the rank of Π could be between zero and two, the number of variables in the system. The appropriate lag structure to use in the VAR was determined from the log-likelihood, Akaike and Schwarz's information criteria, and the F-statistic for comparison of the restricted and unrestricted models. We selected an autoregressive model of order (3) as the appropriate lag structure. The maximum eigenvalue statistic for no cointegrating vector (rank =0) was 0.0058 and the trace statistic was 15.93. The 95 percent critical value for the trace statistic was 12.53, implying that the null hypothesis of no cointegrating vector could be rejected. Successively, the null hypothesis of at most 1 cointegration relation (rank = 1) was tested. The maximum eigenvalue for r=1 was 0.0014 and the trace statistic (3.04) was lower than the 95 percent critical value (3.84), indicating that the null hypothesis could not be rejected. We concluded that there is one cointegrating vector between credit spreads and the FTSE All Share Return index and the normalised cointegrated relation can be written as follows:

$$CS + 0.003165 * Log(P^{FTSE}) = 0. \tag{10}$$

As cointegrated variables CS and P^{FTSE} are characterised by time paths influenced by any deviation from the long run equilibrium. If the sum of CS and P^{FTSE} is large relative to the long run relationship, either the FTSE must fall ultimately relative to the CS, or CS must fall relative to the FTSE. Without a full dynamic specification of the model, we cannot determine which of the two possibilities will eventually occur. But we know that the short run dynamics must be influenced by the deviation from the long run relationship. According to this result, we will add an error correction variable (ECM) to the dynamic models we will present later on, so that they will actually be error correction models. If the error correction component will result to be statistically significant, this will consolidate the cointegration analysis results and demonstrate the importance of the long-run relationship. We conclude this section, focusing the reader's attention on Figure 5 and, in particular on the clear change in the slope of the long run relation around mid eighties, which suggests the possibility for a further investigation about the presence of a nonlinear cointegration relationship.[7]

4. Modeling credit spreads

The time-series properties of credit spreads broadly discussed in the previous section provide strong evidence for nonlinear dependence, changing volatility, and high levels of intertemporal dependence in the credit spreads generating process. We will carry on our analysis on the basis of these results by modeling the credit spreads process as time dependent. As credit spreads are proved to be non stationary, and since in this case asymptotic distributions are never achieved, they would produce not reliable statistical results. For this reason we will concentrate on the behaviour of credit spread changes.

In this section we will proceed going through the last two stages of the Box-Jenkins methodology. In the estimation stage different models are fitted and parameters estimated. In the diagnostic checking stage models are compared using the parsimony principle (AIC, SBC tests…), *t*-statistics, stationarity and invertibility tests. We will start with modeling credit spread changes as a simple OLS model and its unability to account for some important features of the data will lead us to introduce more complex models, namely autoregressive heteroskedastic models.

ARCH techniques to model interest rate data have specifically been applied to the term structure of interest rates. In particular ARCH models were estimated on corporate bond yields (Weiss, 1984) and on the differential returns between bills with different maturities (Engle, Lilien and Robins, 1987; Engle, Ng and Rothschild, 1990); ARCH-M specifications were applied to the term premium by Engle, Lilien and Robins (1987). However, applications of ARCH or GARCH models to credit spreads have never been implemented so far.

[7] For the interested reader we recall that the basic concept underlying this theory is that the error correction term derives from the nonlinear combination of two or more integrated variables. For details on nonlinear cointegration we advice to see the pioneer work in this field by Granger and Hallman (1991), successively extended by Haekfe and Helmenstein (1996), Escribano and Granger (1998), and Markellos (1998).

4.1. The OLS model

The first model we introduce for credit spread changes is a simple homoskedastic model. After taking into consideration all the financial variables presented in Section 3.3, we used the adjusted R^2 criterion, the Akaike and Schwarz information criteria, and the likelihood ratio (LR) test to select the most parsimonious model. The White (1980) heteroskedasticity consistent method was used to estimate the coefficient covariance matrix. The results and the main diagnostic tests are presented in Table 6 and 7, respectively. The first and the second order autoregressive parameters are estimated to be -0.31 and -0.074, respectively, and both are significantly different from zero at the 1 percent significance level. Credit spread changes are negatively and significantly influenced by the return on the FTSE All Share index lagged one period (R^{FTSE}_{t-1}) with a coefficient of -0.021 and by the contemporaneous change in the term spread ($\Delta TERM_t$) with a cofficient of -0.017. The change in the exchange rate against the dollar ($\Delta DOLLAR_{t-1}$) lagged one period has a positive impact, with a parameter estimate of 0.011. All the signs are as expected.

We first test for *parameter estimates stability*. The plot of the recursive coefficient estimates -which shows the evolution of estimates for any coefficient in the OLS model as more and more of the sample data are used in the estimation- produces no indication of instability. None of the coefficients displays significant variation or jumps typical of a structural break. We notice, however, that most of the coefficients show either a small drop or a spike in correspondence of the end of 1992. The Chow's breakpoint test was implemented in order to see whether the event of the exit from the EMS on September 16, 1992 represents a structural break. The idea of this test is to split the sample in correspondence of the potential break, fit the equation separately for each subsample and chech for any significant difference in the estimated equations. The results of the test are presented in Table 5. Neither the *F* test nor the Loglikelihood Ratio statistic rejects the null hypothesis of no structural change. Moreover, to reflect a possible structure break, a dummy variable was included for September 1992, and lagged one month to encompass any anticipation effect. The dummy coefficient estimate was positive (0.0011) but not significant (t=1.22), confirming the absence of any structural break.

Two additional tests for parameter stability are developed: the CUSUM test based on the cumulative sum of the recursive residuals, and the CUSUM of squared residuals. The first test indicates no parameter instability as the cumulative sum of the recursive residuals lays always within the 5 percent critical lines. The CUSUM of squared residuals is suggestive of residual variance instability since the cumulative sum of the squared residuals periodically lies outside the area between the two (parallel) critical lines. Specifically significant departures from the confidence intervals are observed in the Octor 1991-June 1994 and April 1995-February 1999 periods.

Serial Correlation tests. From the autocorrelation and partial autocorrelation functions of the standardised residuals, we observe that the OLS model is able to remove serial correlation in the residuals only up to lag 5 (Table 7). The Breusch-Godfrey Lagrange multiplier test for serial correlation was also implemented. The null hypothesis of no serial correlation in the residuals up to lag 20 could not be rejected.

The White's test for heteroskedasticity in the residuals was also applied. The test statistic was equal to 287, which is significantly higher than the critical value at any significance level. This implies that the null hypothesis of no heteroskedasticity is to be rejected. But since the null hypothesis assumes that the errors are both homoskedatic and independent of the regressors, and that the linear specification of the model is correct, the high value of the test statistic might be due to the failure of any one of these conditions.

ARCH effects tests. Both the Ljung-Box *Q*-statistic for the squared residuals and the ARCH LM test up to lag 20 in Table 7 indicate the presence of strong ARCH effects in the residuals. The presence of ARCH effects in the residuals obtained from the OLS regression may lead to serious model misspecification if it is ignored. As with all forms of heteroskedasticity, the analysis will result in inappropriate parameter standard errors, which will be typically too small. As a consequence the equation for credit spread changes should be re-specified.

4.2. GARCH Models

Generally, it is argued that the lack of independence arises from the presence of nonlinearities in the series. The dependence between the series and its past history raises the issue of how to summarise such dependence in a useful way. One way is to treat functions of ΔCS as being determined by models such as ARMA, ARCH or GARCH. Defining the expectation of a random variable conditioned upon its past history as E_{t-1}, these models make E_{t-1} ($g(\Delta CS_t)$) a function of ΔCS_{t-1} ($j>0$). When $g(\Delta CS_t) = \Delta CS_t^2$, and E_{t-1} (ΔCS_t) = 0, E_{t-1} (ΔCS_t^2) = σ_t^2 which we indicate as the conditional variance of ΔCS_t. Having generated ΔCS_t^2 by such models makes σ_t^2 potentially dependent upon the past.

As we have seen in Table 4 the squares of credit spreads are correlated and the slow decline in the autocorrelation coefficients may be used to argue that the correlation is very persistent, and that ΔCS squared possess long-memory. In order to capture the ARCH effects and to represent the observed autocorrelation structure in daily credit spread changes, we estimate a number of conditional heteroskedastic time series models. GARCH (p, q) models with different values of p and q are tested from 1,0 to 3,3 by applying likelihood ratio tests successively until the improvement in the likelihood function becomes insignificant.

Non linear optimisation techniques are used to calculate the maximum likelihood estimates based on the Berndt-Hall-Hall-Hausman (BHHH) algorithm. Since we suspect the residuals are not conditionally normally distributed, the quasi-maximum likelihood covariances and robust t-statistics are calculated using the Bollerslev and Wooldridge (1992) procedure.[8]

4.2.1. ARCH(4) Model

A simple ARCH(4) process is firstly fitted to daily credit spread changes (see Table 7). The fourth order of the process is found by using the information criteria mentioned above (the Schwarz information criterion and the Likelihood Ratio test). The mean equation does not differ from the mean equation in the OLS and all the variables maintain the same sign as before. As far as the variance equation is concerned, the estimate of the constant term (α_0) is positive and smaller than the sample variance obtained in the OLS model. This is due to the changing conditional variance over time and its eventual contribution to the unconditional variance. The sum of the other ARCH parameters ($\alpha_1+\alpha_2+\alpha_3+\alpha_4$) is substantially smaller than unity (0.67), indicating that the fitted model is second-order stationary and that at least the second moment exists (Bollerslev, 1986). Finally, the ARCH model is able to totally remove the serial correlation in the residuals but not in the squared residuals. The Q^2 stats

[8] Non robust standard errors would tend to under-estimate the true parameter estimator uncertainty and in the case of GARCH-M models, the GARCH-M parameter would tend to become significant.

and the Lagrangean multiplier reject the presence of significant ARCH effects left only up to lag 5.

4.2.2. GARCH (1,1)

In order to find a more parsimonious specification for the dCS process we model credit spread changes as a GARCH process. Within the class of GARCH processes, we first estimated a simple GARCH (1,1) incorporating first-order GARCH effects in the residuals ε_t. The mean equation is similar to the OLS and ARCH(4) specifications. The GARCH persistence parameter (β) and the ARCH parameter (α_1) are estimated to be 0.826 and 0.115, respectively, with their sum slightly below unity –necessary condition for stability to hold-. So the stationary GARCH formulation seems adequate to model the time variant credit spread changes volatility. However, the degree of persistence in shocks to volatility - given by the sum of the coefficients $a_1 + b$ - is quite high, which implies that shocks to the Eurobond market have highly persistent effects and the response function of volatility decays at a relatively slow pace. The volatility of credit spread changes is driven mainly by the observed squared changes in credit spreads on the previous trading day –as indicated by the size of the GARCH coefficient, which measures the long-term persistence in volatility[9]. With respect to the estimates of the other parameters in the model, all the variables mantain the same sign and approximately the same magnitude as before except for the Return on the FTSE index and the exchange rate parameters which become significant at the 1 percent level. The maximised loglikelihood showed an increase of 214 points over the homoskedastic model and the loglikelihood ratio (LR) strongly rejects homoskedasticity at better than the 1 percent level. Being able to remove the ARCH effects also after lag 5, the GARCH model represents an improvement over the ARCH model, with generally better diagnostic tests.

4.2.3. GARCH (1,1)-Component

We proceed introducing additional variables in the variance equation of GARCH (1,1) in order to test whether they are helpful in reducing the degree of persistence of volatility. In particular we found that the credit spreads level is good for our purpose. We leave the mean equation unchanged as before and we focus on the variance equation parameter estimates. Credit spread level is proven to be an important source of time variation in volatility and

[9] Note also that only persistent changes in volatility are associated to an adjustment in the risk premium.

volatility itself shows to be directional, rising in periods of rising credit spreads. Respect to the previous GARCH models, this new model shows to have a better goodness-of-fit, lower kurtosis in the standardised residuals, and higher loglikelihood value. The sum of the ARCH and GARCH coefficients decreases indeed to 0.87. The tests for serial correlation and for ARCH effects are even more strongly rejected. Despite these improvements, non-normality in the residuals is still quite strong.

Finally, we tested if this second-order system admits periodic solutions, that is if the following relation holds:

$$\alpha_1 < -\beta^2/4 \tag{11}$$

Substituting the paramer estimates we obtain -0.082 < -0.027, which is a standard result implying periodic cycles (Bidargota, 1996). Further and more formal tests might be applied to confirm this preliminary piece of evidence.

To corroborate our general results we finally have replaced changes in credit spread as defined in Eqs. (3)-(4) with changes in relative credit spreads (ΔrCS) following the methodology in Longstaff and Schwartz (1995). We have run the same regressions introducing this new dependent variable and we compared the new estimates with the previous ones. The signs and the magnitude of the new coefficient estimates are similar to the previous parameter estimates. The R^2s of the new specification are generally slightly lower than those presented in Table 6, ranging from 0.272 to 0.289. The DW values also appear to be lower in the new regression specifications. The standardised residuals mean and kurtosis coefficients result to be larger when taking into considerations relative CS. We can generally conclude that changes in credit spreads and changes in relative spreads lead to similar results, however the presence of slightly better diagnostic statistics in the "simple" model specification might be a reasonable argument to prefer it to the "relative" counterpart.

4.2.4. Additional Tests

Summarising, we have found that estimates of the variance equation provide strong evidence of changing conditional volatility for credit spread changes. In all the models presented the estimated sum of the GARCH coefficients ($\alpha_1+\beta$) provides a measure for the persistence of volatility since expected future volatility decays towards the unconditional variance σ_e^2 according to the equation:

$$\sigma_e^2 = \frac{\alpha_0}{1-(\alpha_1+\beta)}\,. \tag{12}$$

The sum $\alpha_1 + \beta$ results to be very close to one. This means that multi-step forecasts from the model will approach the unconditional variance quite slowly: the estimated mean lag of this variance expression, $1/(1-\beta)$, ranges between 4 to 6 days. Another way to view the volatility persistence is by calculating the half life of volatility shocks, which is computed as $\ln(0.5)$ over $\ln(\alpha+\beta)$. The half-life of volatility shocks ranges from 2 to 10 days.

As a final comparison of the performance of the various models, we analysed the residuals from the various models and their 95 percent forecast intervals $\pm$ 1.96 $(h_t)^{1/2}$. Residuals appear to be almost indistinguishable, indicating that any model may not provide a significant improvement over the others in terms of point forecasts. The forecast intervals, however, are very different. In particular, it emerges that the conditional variance derived from the GARCH (1,1)-component model seems to reflect more accurately the behaviour of the series. During periods of low volatility, such as before 1992 and from 1996 to 1997 the forecast intervals of the ARCH model frequently decline to the lower bound $\pm 1.96\ (\alpha_0)^{1/2}$. However, for both the GARCH models, during the same periods, the forecast intervals become smaller than $\pm 1.96\ (\alpha_0)^{1/2}$. As we should expect from a good conditional variance model, the series can be predicted with higher confidence during less volatile periods. Therefore, from the confidence intervals analysis, the GARCH(1,1) models appear to be most attractive, confirming results in Table 7.

4.3. Asymmetric Analysis

The main limitations of the GARCH model derive from the property of linearity and from the quadratic form of the conditional variance that this model displays. The impact of past values of the innovation on the current volatility is only a function of their magnitude and not of their sign. However, we might expect bad news have a bigger impact on the predictable volatility of CS than good news of similar magnitude, we therefore proceed testing this hypothesis.

The simplest approach to examine the eventual dependence of the conditional volatility of $\Delta CS(t)$ upon the past is to plot $(\Delta CS_t - \mu)^2$ against CS_{t-1}, which is done in Figure 6.a. The evidence of a level effect it's not very clear. Alternatively, we can look at the cross correlation between the squared standardised residuals and lagged standardised residuals. These cross correlations should be zero for a symmetric GARCH model and negative for asymmetric GARCH models (TARCH or EGARCH). From Figure 6.b it emerges that volatility does not depend upon the sign of credit spread changes; in fact, neither the magnitude of the correlations is high, nor the sign is persistent over time. However, the cross correlation only picks up linear associations between the two series and may miss nonlinear dependence between the two series.

As an alternative approach to check for any level effect we can investigate if the observed conditional heteroskedasticity in the data might be better accounted for by an asymmetric GARCH process -TARCH or EGARCH. The Threshold GARCH (TARCH) model was introduced by Zakoian (1990) and Glosten, Jagannathan and Runkle (1993), and it differentiates from a GARCH model since the quadratic form of the residuals in the standard GARCH is replaced by a linear function, allowing for different reactions of volatility to the sign of the past errors. Another useful parameterisation is the exponential GARCH (EGARCH) introduced by Nelson (1991):

$$log(s_t^2) = a_0 + b_1 \, log(s_{t-1}^2) + a_1 \left(\left| \frac{e_{t-1}}{s_{t-1}} \right| - \sqrt{\frac{2}{p}} \right) + g \, \frac{e_{t-1}}{s_{t-1}} \qquad (13)$$

where the parameter γ is essentially the parameter that allows for asymmetry. If γ is not significantly different from zero, then a positive surprise has the same effect on volatility as a negative surprise of the same magnitude. If $\gamma > 0$, a negative surprise ($\varepsilon > 0$) increases volatility more than a positive surprise ($\varepsilon < 0$). Note that a bad news in the case of credit spreads is identifiable by a positive shock $\varepsilon > 0$. If $\varepsilon > 0$ the credit spread level increases and the credit risk as well. That is why we expect $\gamma > 0$ if volatility increases with bad news ($\varepsilon > 0$).

From the estimation of the TARCH (1,1) and EGARCH (1,1) we obtain values for the parameter γ -representing the leverage effect term- not significantly different from zero. A graphical and more intuitive presentation of these results is given by the news impact curve. This curve relates past credit spread changes shocks (news) to current volatility and measures how new information is incorporated into volatility estimates. In other words, the curves show whether the volatility of the two subsets reacts in the same manner after a bad or good unexpected event. The news impact curve for a TGARCH (1,1), for example, is given by:

$$\sigma_t^2 = A + \alpha_1 \cdot \varepsilon_{t-1}^2 \text{, for } \varepsilon_{t-1} < 0 \tag{14}$$

$$\sigma_t^2 = A + (\alpha_1 + \gamma) \cdot \varepsilon_{t-1}^2 \text{, for } \varepsilon_{t-1} > 0 \quad \text{where} \tag{15}$$

$$A = \alpha_0 + \beta_1 \cdot \sigma_{Un}^2 \tag{16}$$

where σ_{Un}^2 is the unconditional variance. From our estimates we obtain that:

$$\sigma_t^2 = -1.93E-06 + 0.203 \cdot \varepsilon_{t-1}^2 \text{ for } \varepsilon_{t-1} < 0 \tag{17}$$

$$\sigma_t^2 = -2.71E-06 + 0.206 \cdot \varepsilon_{t-1}^2 \text{ for } \varepsilon_{t-1} > 0, \tag{18}$$

which can be represented in Figure 6.c and 6.d equivalently. We can see how bad news ($\varepsilon > 0$) have just slightly bigger impact on conditional volatility -steeper slope for the positive side.

4.4. Summary results

The explanatory power of linear and nonlinear models is very similar with adjusted R^2 around 30 percent. The variables that have shown to be able to explain changes in credit spreads are the two autoregressive terms, the return on the FTSE All Share index (lagged one period), the change in the exchange rate against the dollar (lagged one period), and the contemporaneous change in the TERM spread. The signs of the estimated coefficients are all consistent with our expectations. Credit spread changes are mainly explained by autoregressive components, which present a negative sign implying mean reversion in the credit spread process. Moreover, credit spreads increase as the slope of the term structure decreases and increase as the sterling appreciates. The return of FTSE in the previous period has a negative impact on credit spreads in the current period. The coefficient of changes in the risk-free short-term rate is negative but not significant either statistically or economically. Finally, credit spreads volatility is increasing with credit spreads level.

A GARCH-M (1,1) model was also estimated with a mean equation similar to the mean equation of previous models except for the presence of an additional term, h, representing the impact of the conditional standard deviation on the conditional mean. The trade-off parameter γ, which is the estimated coefficient for the h term, can be interpreted as the coefficient of relative risk aversion according to Merton (1980) and Campbell and Hentschel (1992). The sign and the magnitude of this parameter depend on the utility functions of the agents and the supply conditions of the assets. Hence, γ can take a positive, negative, or a zero value (Engle et al 1987). Note also that γ is not the price for systematic risk, that is the price for the risk component that cannot be diversified. If fluctuations in volatility are mostly due to shocks to the unsystematic risk, γ can have any sign. In other words, an increase in the conditional variance, which is a measure for the total risk, need not be accompanied by an increase in the risk premium. The GARCH-M parameter is positive but not significant. Volatility, therefore, does not contribute to the premium for credit risk.

We also tested whether among the other explanatory variables the error correction mechanism (ECM) is significant and if its coefficient is negative as we expect in accord with convergence toward the long-run equilibrium. To this aim we included the ECM in the mean equation interpreting its coefficient as a speed of adjustment parameter. If credit spreads start to increase more rapidly than is consistent with the steady state solution, the term $\{cs(-1 +0.003165*Log(P_{FTSE}(-1))\}$ increases, but since the coefficient is less than zero, the overall effect is to slow down the short term growth in credit spreads, forcing credit spreads at time t back towards their long run growth path. In other words, changes in credit spreads partially correct last period's disequilibrium and move towards the new equilibrium in response to movements in its determinants (long-term interest rates, return index on the FTSE All Share index and short-term interest rate conditional volatility). In fact we found that the estimated ECM coefficient in the mean equation is actually negative but not significant. This does not convalidate the cointegration analysis before developed, which is a confirmation that a deeper and more appropriate methodology should be applied to shed some light on the credit spreads long-term relationships.

5. Conclusions

The main results of our investigation about the behaviour of credit spreads on the sterling Eurobond index can be summarised as follows. Credit spreads show to be characterised by a cyclical behaviour and by a clustering of outliers across time, which is symptomatic of a persistent volatility process. This argues against homoskedastic models for credit spreads in favor of conditionally heteroskedastic models. The unconditional distribution of both credit spreads levels and changes is more peaked and displays fatter tails than a normal distribution. Short-run co-movements with the main financial and economic variables are measured by correlation coefficients. Changes in credit spreads appear to be negatively correlated with interest rates variables, and with the exchange rate against the dollar. On the other hand, credit spreads are positively correlated with variables proxy for the consumer confidence or business cycle. From the intertemporal stationarity analysis credit spreads result to be integrated of order 1, and long-run comovements (cointegration) are weakly observed with the FTSE All Share Price index. Moreover, credit spread levels and changes are proved not to be an *i.i.d.* process and from the autocorrelation structure analysis a few stylised fact emerged: short-term dependence, nonlinearities and persistence in the conditional variance. The evidence, hence, suggests nonlinear dynamics and time-varying volatility structure.

We estimated linear and nonlinear models to identify the factors driving changes in credit spreads. Our results show that the factors suggested by traditional models of default risk explain 30 percent of the variation in credit spreads as measured by the adjusted R^2. We find that the signs of the coefficients of the explanatory variables are in line with what the analysis would predict. An increase in the return on the FTSE leads to a contraction in credit spreads. Eurobond spreads are positively related to the exchange rate and negatively related to the slope of the term structure. The ECM, as derived from the cointegration analysis, was added in the model, but its estimate was found not significant.

The analysis of the residuals shows that nonlinear models remove the autocorrelation but cannot fully account for the leptokurtosis they reveal. The study also finds a preliminary piece of evidence in favor of periodicity in the time series of changes in credit spreads.

Finally, no statistically significant evidence of asymmetries in the persistence of positive and negative shocks is documented.

Our empirical results contribute to understanding the time series process of credit risk. This has implications for term structure models of corporate yields, the pricing of credit derivatives, and methods for measuring credit risk. Our investigations can be refined by further exploring the long memory structure of credit spreads in the presence of nonlinearities and by a future investigation about the presence of periodic cycles, which might be exploited for forecasting purposes. It remains also to be investigated whether GARCH models with thick-tailed errors can account for *all* the leptokurtosis observed in the data. The hypothesis of a mixture of normal distributions - that might explain both the shape of the densities and the excess kurtosis of the data- and the nonlinear cointegration hypothesis might also be the focus of new research in the field of credit spreads.

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Table 1
ISMA Eurobond Index Composition over time, 1992-1999.

The ISMA Eurobond Index has been broken down by country of the issuer, maturity of the issue, and credit rating of the issuer. The data are expressed as percentages of the total market volume of Eurobonds issued in the respective year.

	1992	1993	1994	1995	1996	1997	1998	1999
Panel A: Origin of Issuers								
UK	69%	68%	62%	59%	61%	54%	51%	50%
Euro	12%	14%	16%	17%	17%	19%	18%	18%
Non-Euro	1%	1%	2%	2%	1%	1%	2%	1%
Japan, Asia & Oceania	6%	5%	5%	6%	5%	5%	4%	4%
USA, Canada & Latin America	3%	3%	4%	4%	3%	8%	10%	10%
Other Internationals	8%	9%	11%	13%	12%	14%	16%	18%
Panel B: Maturity Structure								
[0, 3)	-	-	-	-	-	3%	11%	16%
[3, 7)	-	4%	14%	21%	32%	46%	37%	30%
[7, 10)	43%	46%	42%	39%	29%	19%	20%	18%
[10, 15)	9%	14%	17%	12%	11%	8%	6%	8%
[15, 20)	15%	9%	9%	9%	10%	8%	8%	6%
[20, 30)	33%	27%	17%	18%	18%	13%	11%	19%
> 30	-	-	1%	1%	1%	3%	6%	3%
Panel C: Rating								
AAA	39%	40%	37%	39%	34%	42%	46%	44%
AA	48%	47%	48%	45%	47%	37%	32%	29%
A	12%	13%	14%	15%	17%	20%	20%	21%
BBB	-	-	-	-	-	1%	-	4%
BB	-	-	-	1%	1%	-	-	1%
B	-	-	1%	1%	-	-	1%	1%

Table 2
Unconditional Daily Distributions

The table summarises the daily distributions of the main variables. The sample covers the period from January 1, 1991 through May 26, 1999, for a total of 2193 observations. Yields on the Eurobond Index are from ISMA Ltd. All the other data are from Datastream International.

	Mean	***Median***	***Max***	***Min***	***Std. Dev.***	***Skewness***	***Kurtosis***	***N***
CS	0.074	0.070	0.199	0.039	0.024	2.035	7.734	2193
DCS	0.000027	0.000	0.024	-0.024	0.004	-0.070	8.791	2192
DDOLLAR	0.000	0.000	0.047	-0.061	0.010	-0.337	6.948	2192
DSHORT	-0.004	0.000	0.531	-0.844	0.074	-2.392	36.61	2192
DLONG	-0.003	-0.001	0.333	-0.556	0.063	-0.065	8.383	2192
DTERM	0.001	-0.001	0.756	-0.775	0.093	0.524	15.75	2192
R^{FTSE}	0.001	0.000	0.059	-0.035	0.008	0.156	6.794	2192
$RY^{EUROBOND}$	8.381	8.410	11.89	5.100	1.582	-0.009	2.460	2192
DMARK	0.000	0.000	0.055	-0.110	0.013	-0.509	7.856	2192
DLT_DY	0.000	0.000	0.125	-0.106	0.018	-0.081	6.885	2192
DDY^{FTSE}	-0.001	0.000	0.180	-0.280	0.031	-0.677	10.26	2192

Table 3
Bivariate Unconditional Daily Correlations

Bivariate correlations between CS and DCS and basic financial variables are computed and measured as Pearson's correlation coefficients with their significance levels in parenthesis.

	CS		DCS
ΔCS	0.083** (0.00) N=2191	**CS**	0.083** (0.000) N=2191
DOLLAR	.230** (0.00) N=2193	**DDOLLAR**	-.032 (0.148) N=2191
PRICE^{FTSE}	.357** (0.00) N=2193	**R^{FTSE}**	0.161** (0.00) N=2191
DY^{FTSE}	-.171** (0.00) N=2193	**ΔDY^{FTSE}**	-.161** (0.00) N=2191
LONG	-.445** (0.00) N=2193	**ΔLONG**	-.676** (0.00) N=2191
LT_DY	-.672** (0.00) N=2154	**ΔLT_DY**	-.474** (0.00) N=2152
SHORT	.122** (0.00) N=2193	**ΔSHORT**	.009 (0.674) N=2191
TERM	-.577** (0.00) N=2193	**ΔTERM**	-.462** (0.00) N=2191

*Note: **, * Correlation is significant at the 0.01 and 0.05 level, respectively (2-tailed).*

Table 4
Autocorrelation structure

Autocorrelation coefficients for lags up to 5, and for lags 10, 20, 40, 70 and 100 are presented for daily CS, ½CS½ and (CS)^2 in Panel A); for daily DCS, ½DCS½ and (DCS)^2 in Panel B and for the realised, absolute and squared daily residuals from the model:

$$? \, cs_t = a + ß_1 ? \, cs_{t-1} + ß_2 ? \, cs_{t-2} + e_t$$

in Panel C. The last two columns reported are the Ljung-Box Q-statistics with their p-values in brackets. The Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k. Under the null hypothesis, Q is asymptotically distributed as a c^2 with degrees of freedom equal to the number of lags. The null hypothesis is rejected at a significant level of less than 1 percent for all lags for both the series CS and DCS.

	r_1	r_2	r_3	r_4	r_5	r_{10}	r_{20}	r_{40}	r_{70}	r_{100}	Q(5)	Q(20)
Panel A												
CS	0.988	0.983	0.977	0.971	0.965	0.940	0.879	0.776	0.719	0.547	10482 [0.00]	38624 [0.00]
½CS½	0.988	0.983	0.977	0.971	0.965	0.940	0.879	0.776	0.719	0.547	10482 [0.00]	38624 [0.00]
CS^2	0.989	0.982	0.974	0.965	0.956	0.924	0.839	0.713	0.689	0.471	10409 [0.00]	37126 [0.00]
Panel B												
DCS	-0.32	0.024	0.007	0.019	-0.006	0.040	0.025	-0.002	0.013	-0.009	227.33 [0.00]	259.59 [0.00]
½dCS½	0.323	0.179	0.191	0.142	0.127	0.133	0.107	0.098	0.087	0.002	460.28 [0.00]	1098.8 [0.00]
DCS^2	0.237	0.121	0.169	0.085	0.078	0.095	0.075	0.061	0.064	-0.001	247.51 [0.00]	578.65 [0.00]
Panel C												
e	-0.003	-0.002	-0.004	0.021	-0.024	0.043	0.015	-0.025	0.01	0.001	2.27 [0.81]	31.22 [0.05]
|e|	0.212	0.179	0.189	0.138	0.118	0.149	0.101	0.081	0.076	0.005	319.73 [0.00]	886.54 [0.00]
e^2	0.135	0.131	0.172	0.081	0.052	0.116	0.057	0.048	0.036	0.001	162.9 [0.00]	516.6 [0.00]

Table 5
The Chow's breakpoint test

The breakpoint Chow test is performed to test for the presence of a structural break. Two test statistics for the Chow test are reported. The F-statistic has an exact finite sample F-distribution if the errors are independent and identically distributed normal random variables. The log likelihood ratio statistic is based on the comparison of the restricted and unrestricted maximum of the (Gaussian) log likelihood function. The LR test statistic has an asymptotic distribution under the null hypothesis of no structural change.

Chow Breakpoint Test: 1/8/1999-30/9/1992			
F-statistic	1.204	Probability	0.30
Log likelihood ratio	7.244	Probability	0.29

Table 6
Linear and nonlinear estimates for daily credit spread changes

The summary parameters and statistics for the linear and nonlinear models for credit spread changes are presented. The sample period is from January 1991 to May 1999 for a total of 2192 observations. The dependent variable is the daily change in the credit spread. In the OLS model the coefficient covariances are corrected for the presence of heteroskedasticity using the White (1980) covariance estimator. All the nonlinear models are estimated under the assumption of not conditionally normally distributed residuals. Robust t-statistics (in parenthesis) are obtained using the method presented in Bollerslev and Wooldridge (1992).

	Expected Sign	OLS	ARCH(4)	GARCH(1,1)	GARCH(1,1) Comp
Mean Equation:					
$C*10^5$		6.850 (0.00006)	-6.730 (0.00005)	6.730 (0.00005)	3.890 (0.00005)
DCS(-1)		-0.310^{***} (0.02865)	-0.385^{***} (0.02395)	-0.307^{***} (0.02246)	-0.331^{***} (0.02221)
DCS(-2)		-0.074^{***} (0.02810)	-0.133^{***} (0.02419)	-0.078^{***} (0.02274)	-0.082^{***} (0.02163)
R^{FTSE}(-1)	-	-0.021^{*} (0.01202)	-0.021^{**} (0.00859)	-0.035^{***} (0.00843)	-0.030^{***} (0.00835)
DTERM	-	-0.017^{***} (0.00151)	-0.015^{***} (0.00106)	-0.015^{***} (0.00117)	-0.015^{***} (0.00115)
DDOLLAR(-1)	+	0.011 (0.00701)	0.013^{**} (0.00535)	0.017^{***} (0.00555)	0.016^{***} (0.00571)
Variance Equation:					
$C*10^6$		-	3.470^{***} ($3.53*10^{-7}$)	0.376^{***} ($1.28*10^{-7}$)	-0.815^{***} ($3.15*10^{-7}$)
Arch(1)		-	0.247^{***} (0.06196)	0.115^{***} (0.02932)	0.121^{***} (0.02846)
Arch(2)		-	0.108^{**} (0.04850)	-	-
Arch(3)		-	0.168^{***} (0.05757)	-	-
Arch(4)		-	0.145^{**} (0.05231)	-	-
Garch (1)		-	-	0.826^{***} (0.04184)	0.754^{***} (0.05069)
CS	+	-	-	-	$2.53*10^{-5\ ***}$ ($7.44*10^{-6}$)

*NOTE: ***, **, * Significantly different from zero at the 0.01, 0.05 and 0.1 level, respectively (using a two-tailed test).*

Table 7
Residuals Diagnostic Checking

Q(5), Q(20) and $Q^2(5)$, $Q^2(20)$ are the Box-Pierce portmanteau test statistics, with 5 and 20 degrees of freedom, applied to the standardised and squared standardised residuals, respectively. They provide a test for the presence of autocorrelation and ARCH effects, respectively. Their P-values are reported in parentheses. In addition the Durbin Watson statistic (DW) for first-order serial correlation and the LM statistic test for the presence of remaining significant ARCH effects are presented. Skewness, kurtosis and the Jarque-Bera test statistic for normality of the standardised residuals are also reported.

Diagnostic Checks	OLS	ARCH(4)	GARCH(1,1)	GARCH(1,1) Comp
as + b	-	0.67	0.93	0.87
Adj. R^2	0.307	0.297	0.304	0.303
Log. Lik.	9668	9882	9915	9943
Mean	-7.64E-20	0.038	-.00067	0.00069
Standard Dev	0.0029	0.999	1.057	0.995
Skewness	0.177	0.217	0.24	0.19
Kurtosis	11.91	7.76	7.53	7.04
Jarque-Bera	7267 (0.00)	2085 (0.00)	1892 (0.00)	1508 (0.00)
DW	2.00	1.85	2.00	1.96
Q(5)	4.558 (0.47)	2.721 (0.74)	5.275 (0.38)	6.324 (0.27)
Q(20)	42.46 (0.00)	23.72 (0.25)	26.75 (0.14)	27.712 (0.11)
LM Arch Test $_{\text{20 lags}}$	13.32 (0.00)	2.338 (0.00)	0.999 (0.45)	0.717 (0.81)
$Q^2(5)$	136.94 (0.00)	3.976 (0.55)	3.065 (0.69)	2.8747 (0.72)
$Q^2(20)$	424.92 (0.00)	47.86 (0.00)	20.50 (0.42)	14.719 (0.79)
Akaike I.C.	-8.82	-9.015	-9.046	-9.072
Schwartz I.C.	-8.80	-8.987	-9.023	-9.046
N	2190	2190	2190	2190

Figure 1.

Time Series of Daily Credit Spread Levels, Changes and Absolute Changes

Credit spreads, defined as the continuously compounded yield differencial between the ISMA Eurobond index and the UK long term (10 year) government bond index, are plotted over the period from 31/12/1990 to 26/5/1999. The time series pattern is also presented for credit spread changes and absolute changes, over the same sample period.

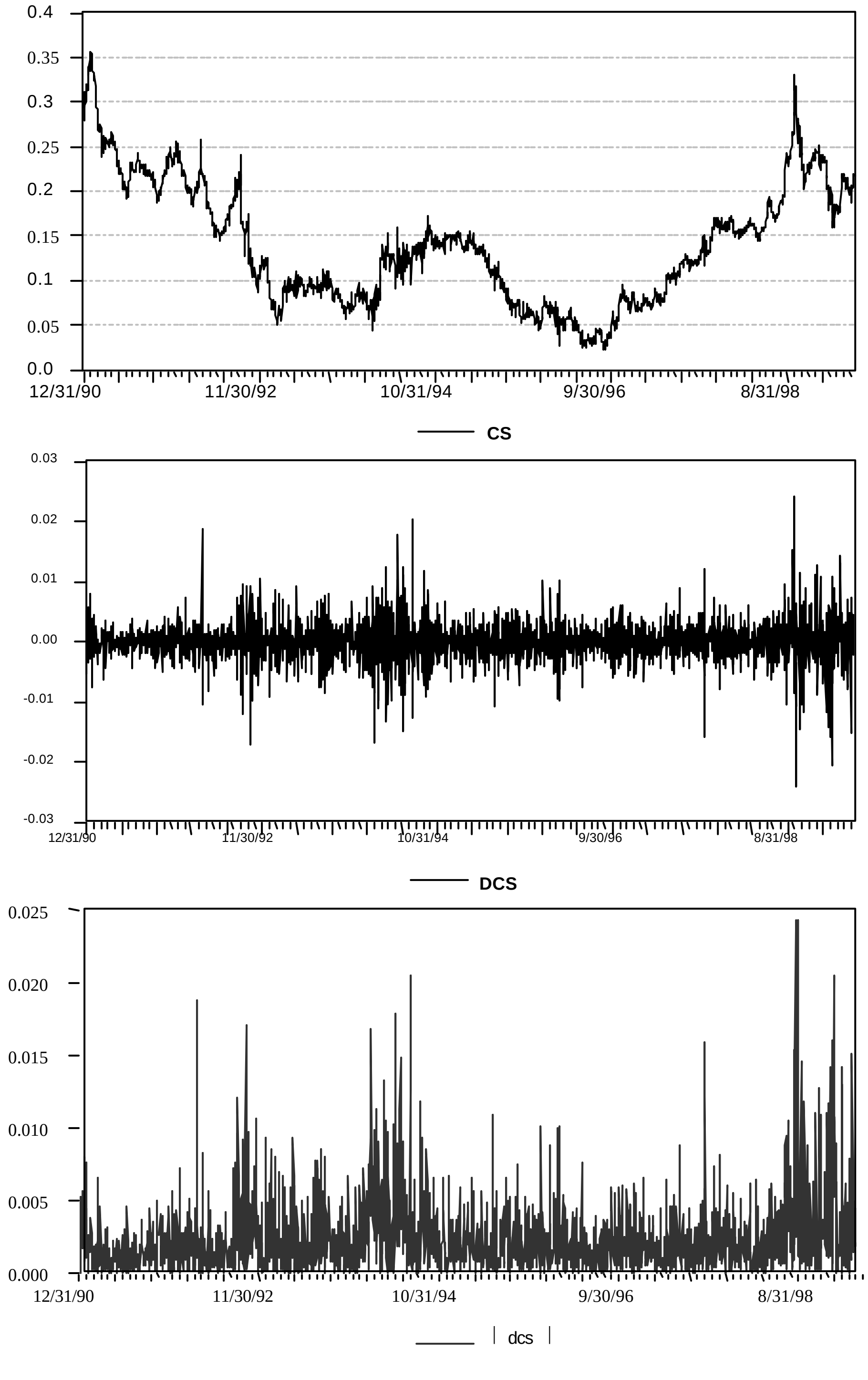
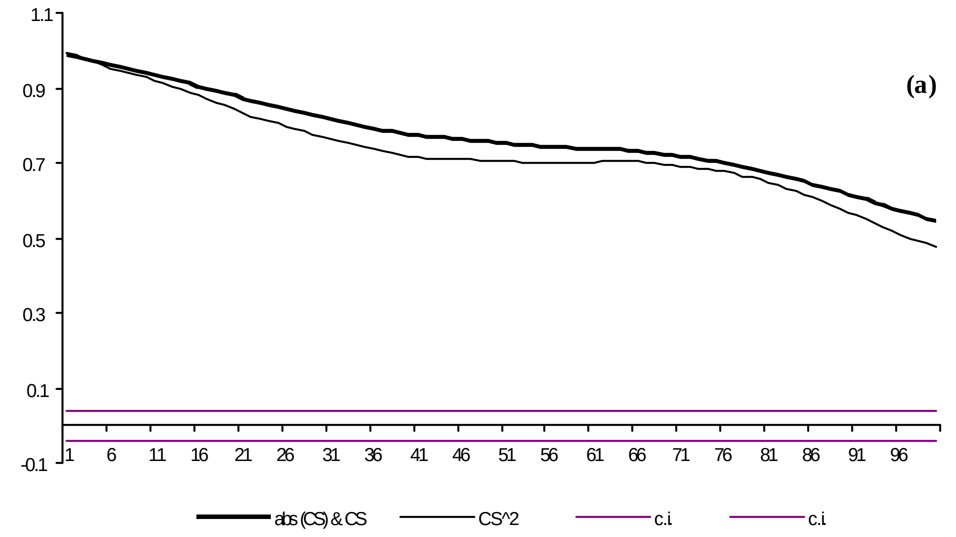


Figure 2

Sample Autocorrelation Function for Daily (a) CS, ½CS½and $(CS)^2$ and (b) dCS, ½dCS½ and $(dCS)^2$.

The autocorrelation function of CS, absolute CS and CS squared is plotted up to lag 100 in part (a). The autocorrelation function for DCS, absolute DCS and DCS squared is also presented in part (b). The dotted lines (c.i.) in the plots of the autocorrelations are the approximate two standard error bounds computed as $\pm 1.96/\sqrt{T}$. Autocorrelation coefficients within these bounds are not significantly different from zero at (approximately) the 5% significance level.



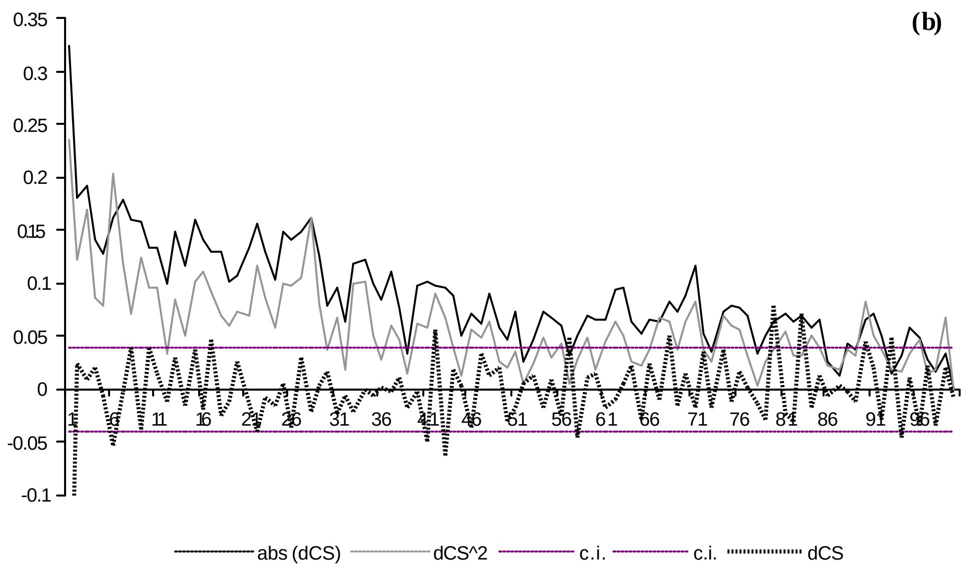
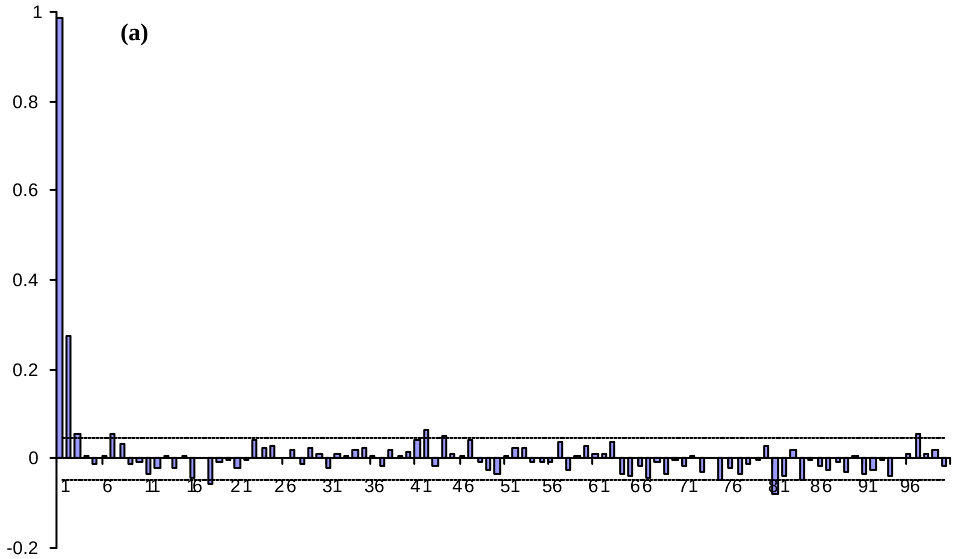


Figure 3

Sample Partial Autocorrelation Function (PAF) for CS and DCS.

The partial autocorrelation at lags from 1 to 100 is plotted both for CS and DCS. The PAF measures the correlation of values that are k periods apart after removing the correlation from the intervening lags. If the pattern of autocorrelation can be captured by an autoregression of order less than k, then the partial autocorrelation at lag k will be close to zero. The dotted lines in the plots of the partial autocorrelations are the approximate two standard error bounds computed as $1.96/\sqrt{T}$. Partial autocorrelation coefficients within these bounds are significantly different from zero at (approximately) the 5% significance level.



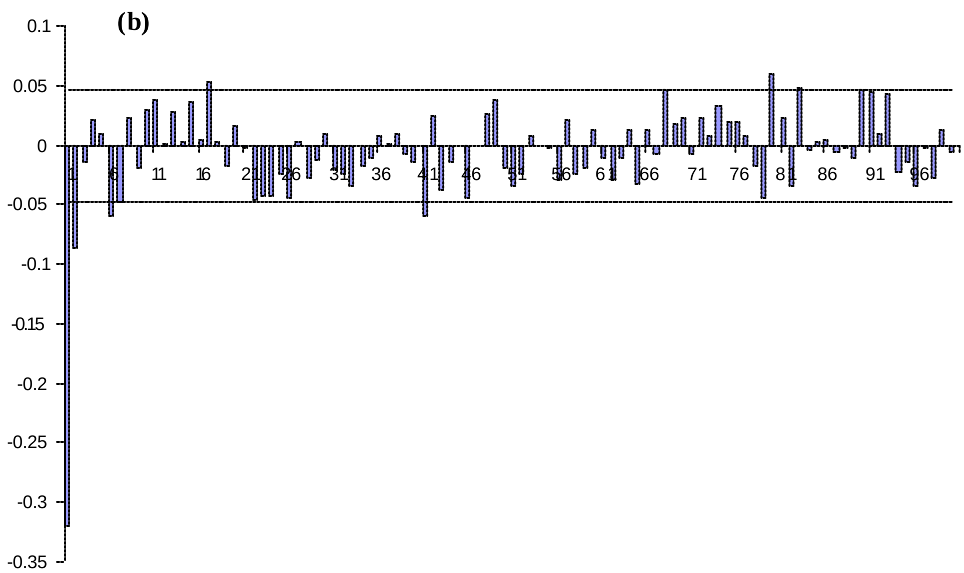
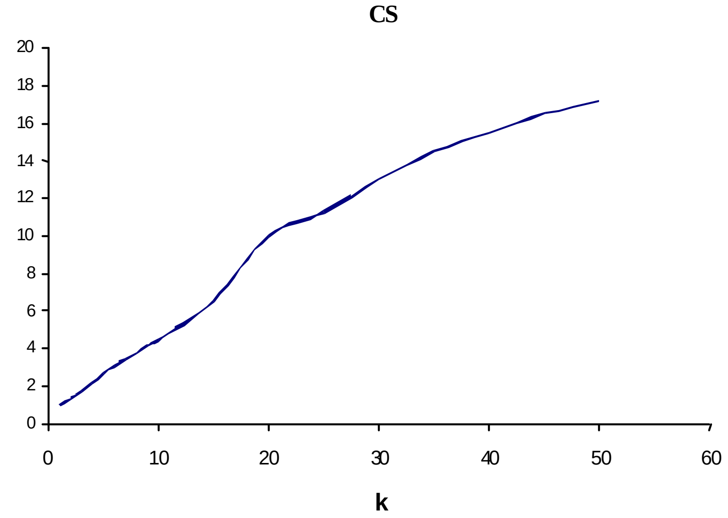


Figure 4

The variance ratio test for stationarity

The variance ratio l is plotted against k periods ahead both for CS and DCS and is computed by dividing the variance of CS (DCS) estimated from longer intervals by the variance of CS (DCS) estimated from shorter intervals, (for the same measurement period), and then normalizing this value to one by dividing it by the ratio of the longer interval to the shorter interval. The variance ratio is an increasing (straight) line if the series presents a unit root. In the absence of a unit root the value of the ratio oscillates around a mean value for any value of k. We can also infer evidence of mean reversion if the variance ratio lies below unity.



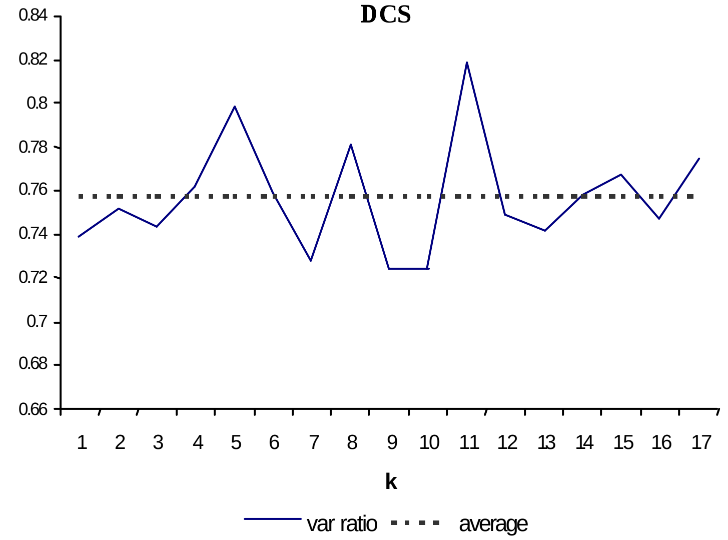


Figure 5

Cointegration between credit spreads and the FTSE All Share Price Index

The CS series is plotted against the Log(FTSE Price) series. A linear negative relationship between the two series is apparent for values of the Log(FTSE Price) series up to 9.3, or in other words up to May 1997, which is also the starting date for the Asian crisis. After this period the relation seems to invert to become positive.

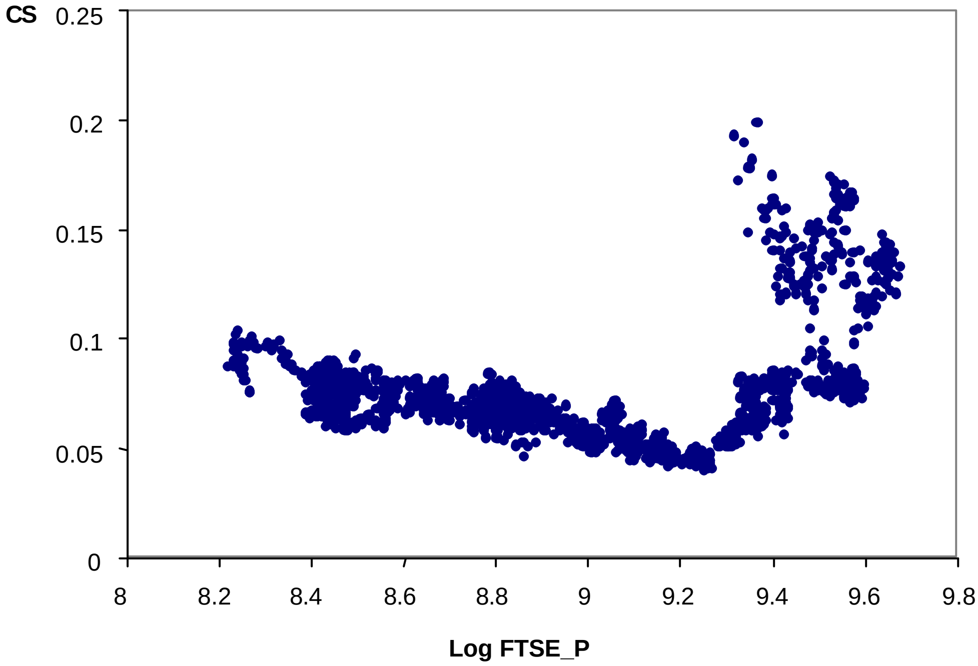


Figure 6
Asymmetric Responses and News Impact Curves

(a) To examine the dependence of the conditional volatility of DCS(t) upon the past we plotted $(DCS_t - m)^2$ against CS_{t-1}. (b) Alternatively, we can look at the cross correlation between the squared standardised residuals and lagged standardised residuals. These cross correlations should be zero for a symmetric model and negative for asymmetric models. Note that the cross correlation only picks up linear associations between the two series and may miss nonlinear dependence.

(c) and (d) We present the news impact curves, which are curves that relate past credit spread changes shocks (news) to current volatility and measures how new information is incorporated into volatility estimates. We can see whether the volatility of the two subsets reacts in the same manner after a bad or good unexpected event. We can see how bad news (e>0) have just slightly bigger impact on conditional volatility with steeper slope for the positive side.