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Are CDS spreads predictable? An analysis of linear and non-linear forecasting models*

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Abstract

This paper investigates the forecasting performance for CDS spreads of both linear and non-linear models by analysing the iTraxx Europe index during the financial crisis period which began in mid-2007. The statistical and economic significance of the models' forecasts are evaluated by employing various metrics and trading strategies, respectively. Although these models provide good in-sample performances, we find that the non-linear Markov switching models underperform linear models out-of-sample. In general, our results show some evidence of predictability of iTraxx index spreads. Linear models, in particular, generate positive Sharpe ratios for some of the strategies implemented, thus shedding some doubts on the efficiency of the European CDS index market.

JEL classification: G01; G17; G20; C22; C24

Keywords: Credit default swap spreads; iTraxx; Forecasting; Markov switching; Market efficiency; Technical trading rules

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1. Introduction

Credit default swaps (CDS) have attracted considerable attention in the finance world since their introduction in the nineties. These financial products allow investors to trade and hedge assets which bear credit risk with a certain ease. In the past, trading credit risk was only possible via the use of bonds. However, shorting credit risk in the cash market is made difficult by the fact that its repo market is not very liquid and the maturity of the agreement is short. These short-sale restrictions in the cash market do not apply to the CDS market, and as such it is usually preferred by investors who want to trade credit risk at a known cost (the CDS spread) and for longer maturities.

Over the last decade, the CDS market has experienced an impressive growth, reaching its peak at the end of 2007 with a notional amount outstanding of about USD 62 trillion. Since then, the market hit by the "Great Recession" witnessed a downward trend and large decrease in amount outstanding. The market has, however, recovered from the subprime-induced financial market turmoil of 2008-2010 and as of August 2012, it boasted an outstanding value of almost USD 25 trillion.[1] The trading volume of CDS indices of approximately USD 8 trillion (as of August 2012) accounts for about a third of the total trading volume of the credit derivatives market.

A CDS index contract is an insurance contract which protects the investor against the default of a pool of names included in the index. Unlike a single-name contract, the default of one member of the pool does not cause the termination of the contract, which instead continues until the maturity but with a reduced notional amount.[2]

Trading of CDS indices was made possible in June 2004, when the Dow Jones iTraxx index family was created. Markit owns, compiles and publishes the iTraxx index series, which include the most liquid European and Asian single-name CDSs. iTraxx Europe is an equally weighted index which comprises 125 single-name investment grade CDSs and is divided into the sub-indices financials senior, financials subordinate and non-financials. Trading of CDS index is available for maturities ranging from 3 to 10 years.

In this paper, we focus on the iTraxx Europe CDS index and address, for the first time in the finance literature, the question of whether CDS index spreads can be forecasted. We focus our attention on the *non-financials* and *financials senior* indices, which are the two main sub-indices of the iTraxx CDS index

[1] See www.dtcc.com for more information on CDS trading data.
[2] The total notional amount of the CDS index contract is reduced by the notional amount of the defaulted entity.

family.[3] Our choice to run a separate analysis on these two indices is explained by the fact that industrial and financial entities are characterised by very dissimilar capital structures.

Clearly, our study would be of interest to both academics and practitioners, who could get a better understanding on the efficiency of the CDS market and the possibility to implement sound hedging models and profitable trading strategies. Whether CDS spreads are characterised by the existence of predictable patterns is an interesting research question whose investigation is useful in terms of asset pricing and credit portfolio management. In addition, single-name credit spreads, and especially CDS index spreads, have become a crucial indicator of the financial conditions of the whole economy and, similarly to the VIX index, of the level of volatility present in the financial markets. These considerations make our study fascinating as well as of common interest for the society as a whole.

While there is an extensive literature which analyses the forecasting performance of econometric models in the equity, bond and foreign exchange markets, the research question of whether CDS spreads can be forecasted has not been directly investigated by previous studies. Hence, our study on the forecastability of CDS spreads extends the literature on CDS spreads. To address our research question, point out-of-sample forecasts are generated from linear and non-linear econometric models.

In particular, we use two linear models, namely a structural model based on ordinary least squares (OLS, hereafter) regression and an AR(1) model as well as the non-linear versions of these models, based on the Markov regime-switching approach. We test the statistical significance of the forecasts obtained, which are discussed at later stages in the paper. We also examine the economic significance of these forecasts by implementing various trading strategies, thus providing inference on the efficiency of the CDS market.

The rest of the paper is as follows: Section 2 reviews the literature. Section 3 describes the dataset. Section 4 presents the forecasting models used in our analysis. Section 5 analyses the in-sample performance of the models used, whereas Section 6 discusses the statistical out-of-sample performance of the forecasting models. Section 7 describes the implementation of the trading strategies used to evaluate the economic significance of the models' forecasts. Section 8 describes the robustness tests and Section 9 concludes our paper.

[3] The remaining two sub-indices are *financials subordinate* and *high volatility*.

2. Literature review

The literature on forecasting asset returns is vast. Great attention has been given to the prediction of stock and bond returns (Keim and Stambaugh, 1986; Fama and French, 1989; Ang and Bekaert, 2007; Cochrane, 2008; Ferreira and Santa-Clara, 2011 and many others). In general, these studies have found that macroeconomic variables, risk measures and price multiples have some predictive power. A considerable number of studies exist on predicting riskless interest rates (Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005; Diebold and Li, 2006; Ludvigson and Ng, 2009, among the others). Recent literature has drawn growing consideration for non-linear predictability patterns of financial assets. Major works on equity returns are by Leung et al. (2000), McMillan (2001), Guidolin and Timmermann (2006) and Guidolin et al. (2009). Relevant studies on interest rates and bond returns include Balke and Fomby (1997), Lekkos and Milas (2004) and Guidolin and Timmermann (2009). Generally, these studies have agreed that non-linear forecasting models accurately describe the in-sample characteristics of financial time series data while less consensus has been reached on the effectiveness of these models for forecasting applications. [4]

Despite the vast proliferation and interest for forecasting various financial assets, little work has instead been done on predicting credit spreads. Apart from Krishnan et al. (2010), whose focus is on an out-of-sample forecasting analysis of firm-level credit spreads, the literature on credit spreads (and CDS spreads) has primarily focused on the development of structural pricing models for pricing a firm's equity and debt as contingent claims on the firm's asset value. The first example of a structural model was introduced by Merton (1974) and subsequent contributions followed.[5] These models assume some stochastic process for the value of a firm's assets and that default occurs whenever the firm's assets value falls below a defined threshold value (or default barrier), which is a function of the outstanding debt of the firm. The value of the firm's debt is obtained by computing its expected future cash flows discounted at the risk-free rate (under the risk-neutral measure). Hence, the CDS spreads, at any point in time, are a function of the firm's assets value, the risk-free rate and some state variables. While this literature on structural credit risk models does not focus on predictability, it instead provides the theoretical framework to identify the

[4] Less evidence of predictability has been found for the exchange rate market for which fundamental variables have unclear predictive power (Engel and West, 2005; Berkowitz and Giorgianni, 2001; Kilian, 1999). Similar conclusions can be reached for a new body of literature on forecasting commodity spot and futures prices (Hong and Yogo, 2012; Gargano and Timmermann, 2014).

[5] See, for instance, Black and Cox (1976), Longstaff and Schwartz (1995) and Leland and Toft (1996). Empirical studies that have analysed the pricing accuracy of structural models (see, for instance, Jones et al., 1984; Eom et al., 2004; Huang and Huang, 2012) have found that, on average, credit risk models under-predict spreads. However, Ericsson et al. (2009) have shown that these models perform better when applied to CDS spreads, namely they are able to replicate spreads observed in the CDS market better than their ability to replicate spreads observed in the bond market.

determinants of changes in credit spreads as well as CDS spreads. Changes in these state variables should then determine changes in CDS spreads. Below is a summary of the theoretical drivers/determinants of credit (and CDS) spreads used by a number of studies (cited below):

1. *The level of the risk-free interest rate*. Longstaff and Schwartz (1995) have shown that a higher spot rate would increase the risk-neutral drift in the firm value process which, in turn, reduces the probability of default and hence CDS spreads.
2. *The slope of the yield curve*. Structural models include one spot rate only; however, the future spot rate is affected by the slope of the yield curve. Hence, an increase in the latter increases the expected future spot rate which, again, should reduce CDS spreads.
3. *The equity returns as a proxy for the overall state of the economy*. Whenever the firm's assets value decreases, the probability of default will increase as there is a higher likelihood of hitting the default threshold. Because a firm's assets value is not directly observable, its equity value can be observed and used as a proxy for the assets value.
4. *The assets volatility*. Higher assets volatility implies a higher probability of default (and higher CDS spreads) as there is a higher likelihood for the asset value process of hitting the default barrier. However, assets volatility is unobservable. Again, we can exploit the positive relationship between the volatility of the assets value and equity volatility and then use the latter as a proxy for the assets volatility.

Collin-Dufresne et al. (2001), Campbell and Taksler (2003) and Cremers et al. (2008) have analysed these determinants of credit spreads and found that they have limited explanatory power. In fact, a common systematic factor (unrelated to macroeconomic and financial variables) is found to be responsible for most of the variation in credit spread changes. Zhang et al. (2009) and Ericsson et al. (2009) have instead focused on the analysis of the determinants of CDS spreads and achieved more encouraging results.[6] In line with the empirical studies on the pricing accuracy of structural models, they have found that the structural variables explain a great deal of the variation in CDS spreads.

These studies on the determinants of spreads are based on a regression analysis which is used to study the contemporaneous relationship between these theoretical drivers (independent variables) and the level or change in credit spread or CDS spread (dependent variable). In the wake of previous forecasting studies on financial assets, the main aim of this paper is instead to investigate whether macroeconomic and financial data (the determinants identified by the theory of structural pricing models) incorporate

[6] All the aforementioned studies used a simple OLS and focussed on spreads obtained for individual firms (rather than indices).

predictive information for future changes in CDS spreads. In particular, we focus our attention on the European iTraxx CDS index.

Two studies have analysed the iTraxx index in the past. Byström (2006) was the first to show that, during the period from June-2004 to March-2006, iTraxx CDS index spread changes presented a positive and significant first-order autocorrelation, which was evident from an in-sample estimation of an AR(1). A simple trading rule which tried to exploit this positive autocorrelation generated positive profits before transaction costs, which turned negative net of trading costs. The second study by Alexander and Kaeck (2008) confirmed Byström (2006)'s findings on the existence of positive autocorrelation of CDS index spreads but also analysed the effect of the theoretical determinants of credit risk in different states of the economy. In particular, they used a Markov switching regression model to explain changes in iTraxx CDS spreads in different regimes over the period from June-2004 to June-2007. Their main conclusion is that option-implied volatilities represent the main determinant of changes in CDS spreads in a volatile regime, whereas in stable conditions equity market returns have a predominant role.

These two studies showed how a Markov switching regression model and an AR(1) model both provide a richer understanding of the in-sample fit of the data. However, the question of whether these models are useful for forecasting future CDS spread changes out-of-sample has not been investigated.

3. The dataset

We download daily quotes of iTraxx Europe CDS indices for *financials senior* and *non-financials* from Bloomberg and focus on the 5-year maturity, which is the most liquid. We cover the data period which goes from 20 September 2005 to 15 September 2010 for a total of 1235 observations for each of the 2 indices. Every six months a new series of iTraxx indices is launched to update the membership of the index such that only the most liquid CDSs are included. In order to base our analysis on the most liquid names at every point in time, we construct a time series for each index which contains the most recent series. Figure 1 shows the times series plots of CDS index spread levels for both *non-financials* and *financials senior* over the whole sample period.

We also download data for the following economic variables, which have been identified as the determinants of CDS spreads by the theory of structural credit risk models: the level of the risk-free interest rate, the slope of the yield curve, the equity return for the iTraxx indices and the asset volatility. We discuss each of these variables individually.

1. As a proxy for the level of the risk-free interest rate, we download Euro swap rates for the 5-year maturity. According to Houweling and Vorst (2005), swap rates are considered as a superior proxy for the risk-free rate than government bond yields.
2. The slope of the yield curve is defined as the difference between the 10-year and 2-year Euro swap rates (see also Collin-Dufresne et al., 2001).
3. As a proxy of the equity return for the iTraxx indices we need to create a portfolio of stocks comprising the same members as the CDS indices. As the CDS indices are equally weighted, we keep an equal weighting scheme even for the stock portfolios. If, for any reason, a firm in the sample lacks information on the traded price, we omit it from the stock portfolio and increase the weight of the other companies in the index equally.
4. We proxy firms' asset volatilities with implied volatilities. Since most of the companies in our sample lack liquid traded options, we use the VStoxx index, which is an implied volatility index of options on the DJ Eurostoxx 50 index.[7]

All forecasting models are estimated over three periods: 20 September 2005 to 31 December 2006; 20 September 2005 to 31 December 2007; 20 September 2005 to 31 July 2008. This allows us to test the stability of the models over a period characterised by different market regimes and simultaneously generate out-of-sample forecasts from the end of the three different periods to 15 September 2010. This way, we are able to test how and whether the various phases of the Great Recession may have affected the forecasting performance of the models.

Table 1 presents the summary statistics for the variables' changes. According to the Augmented Dickey Fuller (ADF) test[8], changes in all variables are stationary. The variables' levels show a positive first-order autocorrelation (not shown), which disappears (for most of them) when first differences are taken. CDS spreads are the most volatile variables and all variables show clear traits of non-normality as confirmed by the Bera-Jarque test and the values assumed by skewness and kurtosis.

4. The forecasting models

4.1 Linear models: Structural Model and AR(1)

Previous studies which analysed the determinants of credit spreads used a set of independent variables (described in Sections 2 and 3) suggested by the theory of structural credit risk models and introduced by

[7] Data on VStoxx is retrievable from www.stoxx.com.
[8] See Dickey and Fuller (1981).

Merton (1974). While these studies focused on the contemporaneous relationship between the credit spreads and the explanatory variables, we are instead interested in the forecasting ability of these variables in predicting future credit spreads. Hence, we use lagged variables to forecast future CDS spreads. We estimate the following regression for each CDS index *i* (with *i*=1 for financials senior and *i*=2 for non-financials):

$$\Delta CDS_t^i = \alpha + \beta_1^i \Delta CDS_{t-1}^i + \beta_2^i \Delta r_{t-1}^5 + \beta_3^i \Delta(r_{t-1}^{10} - r_{t-1}^2) + \beta_4^i EQUITY\_R_{t-1}^i + \beta_5^i \Delta V_{t-1} + \varepsilon_t^i \quad (1.1)$$

where ΔCDS_t^i is the daily change in the *i*th CDS index. Δr_{t-1}^5 is the change in the 5-year Euro swap rate, $\Delta(r_{t-1}^{10} - r_{t-1}^2)$ is the change in the slope of the yield curve (which is proxied by the difference between the 10-year and the 2-year Euro swap rates), $EQUITY\_R_{t-1}^i$ denotes the return on the *i*th stock portfolio and ΔV_{t-1} is the change in the VStoxx volatility index.

The study by Byström (2006) found a positive autocorrelation in iTraxx CDS index spreads, thus prompting us to also investigate the forecasting power of a simple AR(1) model, which is a reduced form of equation (1.1). This will enable us to find whether future CDS spreads can be forecasted by using information on past CDS spreads only:

$$\Delta CDS_t^i = \alpha + \varphi^i \Delta CDS_{t-1}^i + \varepsilon_t^i \quad (1.2)$$

We would like to reiterate that previous studies which have used these models have done so in order to either explain changes in credit spreads and study the contemporaneous correlation existing between the dependent variable and the independent variables (this is the case for the structural model) or analyse the in-sample performance of the forecasting model (as for the AR(1)). Hence, no attempt has been made to test the out-of-sample performance of these linear models. This is the main objective of our analysis.

4.2 Non-linear models: Markov Switching Structural Model and Markov Switching AR(1)

The aforementioned linear models in equations (1.1) and (1.2) are extended to allow switching in the explanatory variables. We follow the Markov regime-switching approach introduced by Hamilton (1994). In these Markov switching augmented models, the effects of these selected explanatory variables on the changes in CDS spreads depend on the CDS market condition or regime. Therefore, the magnitude of the effect of changes in the right-hand-side variables depends on whether the CDS market is in a high-volatility or low-volatility regimes. Given these, equation (1.1) is now transformed mathematically as:

$$\Delta CDS_t^i = \alpha_{S_{t-1}} + \beta_{S_{t-1},1}^i \Delta CDS_{t-1}^i + \beta_{S_{t-1},2}^i \Delta r_{t-1}^5 + \beta_{S_{t-1},3}^i \Delta(r_{t-1}^{10} - r_{t-1}^2) + \beta_{S_{t-1},4}^i EQUITY\_R_{t-1}^i + \beta_{S_{t-1},5}^i \Delta V_{t-1} + \varepsilon_{S_t}^i \quad (1.3)$$

where $\varepsilon_{S_t,t} \sim N\left(0, \sigma_{S_t}^2\right)$

and $S_t = j$ (for j = 1 or 2)

In this Markov regime-switching augmented version of equation (1.1), the term S_t is the latent state variable. This could equal 1 or 2 depending on whether or not the CDS market is in a high or low volatility regime, thus, implying that the impact of the explanatory economic variable on CDS spreads depend on the CDS market condition. Our choice of selecting two regimes is based on the fact that most studies that have sought to explain the dynamics of the CDS spreads using Markov switching models have opted to use only two regimes (representing a low-volatile and high-volatile market regimes) including Alexander and Kaeck (2008) who were the first to introduce Markov switching models for the iTraxx CDS index.[9] In a two-regime Markov switching model, a first-order Markov chain with fixed transition probability matrix (P) governs the latent state variable S_t:

$$\mathrm{P} = \begin{bmatrix} \Pr\left(S_t = 1 \mid S_{t-1} = 1\right) & \Pr\left(S_t = 2 \mid S_{t-1} = 1\right) \\ \Pr\left(S_t = 1 \mid S_{t-1} = 2\right) & \Pr\left(S_t = 2 \mid S_{t-1} = 2\right) \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{1.4}$$

where p_{jk} are the transition probabilities from state j to state k.

A maximum likelihood procedure is used to estimate the Markov switching model and assuming that the error term has a normal distribution, the density of the dependent variable conditioned on the regime is given as:

$$\eta_{i,t} = f\left(\Delta CDS_t \mid S_t = j, X_t, \Omega_{t-1}; \theta\right) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left\{ -\frac{\left(\Delta CDS_t - X'_{t-1}\beta_j\right)^2}{2\sigma_j^2} \right\} \tag{1.5}$$

where, $\Omega_{t-1} = \left(\Delta CDS_{t-1}, \Delta CDS_{t-2}, \ldots, X_{t-1}, X_{t-2}, \ldots\right)$ represents all the past information to time t–1, θ is the vector of parameters $\left(\beta_{S_t,0}, \beta_{S_t,1}, \beta_{S_t,2}, \beta_{S_t,3}, \beta_{S_t,4}, \sigma_{S_t}^2, p_{11}, p_{22}\right)'$ to be estimated and X'_t represents the vector of explanatory variables. Therefore, the conditional density at time t is obtained from the combined density of ΔCDS_t and S_t:

$$f(\Delta CDS_t \mid \Omega_{t-1}; \theta) = f(\Delta CDS_t, S_t = 1 \mid \Omega_{t-1}; \theta) + f(\Delta CDS_t, S_t = 2 \mid \Omega_{t-1}; \theta) \tag{1.6}$$

[9] Other studies that have opted to use two-state Markov regime models to study CDS spreads include Kim et al. (2008), Dionne et al. (2011), Guo and Newton (2013), Chan and Marsden (2014) and Guo et al. (2011).

which is equivalent to:

$$\sum_{j=1}^{2} f(\Delta CDS_t \mid S_t = j, \Omega_{t-1};\theta) P(S_t = j \mid \Omega_{t-1};\theta) \tag{1.7}$$

Markov switching models allows us to make inferences as to what regime the CDS market is in by generating filtered probabilities which are calculated recursively. The filtered probabilities are computed using information up to time *t* and as such are dependent on real-time data:

$$\xi_{kt} = \Pr(S_t = k \mid \Omega_t;\theta) = \frac{\sum_{i=1}^{2} p_{jk}\xi_{i,t-1}\eta_{kt}}{f(\Delta CDS_t \mid \Omega_{t-1};\theta)} \tag{1.8}$$

Note that the Markov switching version of equation (1.2) is computed using the exact same approach and defined as:

$$\Delta CDS_t^i = \alpha_{S_{t-1}} + \varphi_{S_{t-1}}^i \Delta CDS_{t-1}^i + \varepsilon_{S_t}^i \tag{1.9}$$

The only difference is that equation (1.5) for the density of the dependent variable now becomes:

$$\eta_{i,t} = f\left(\Delta CDS_t \mid S_t = j, \Delta CDS_{t-1}, \Omega_{t-1};\theta\right) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left\{-\frac{\left(\Delta CDS_t - \phi_j \Delta CDS_{t-1}\right)^2}{2\sigma_j^2}\right\} \tag{1.10}$$

A forecast from these Markov switching models can be made as follows:

$$\Delta CDS_{t+1}^e = (\hat{\xi}_{1t}\hat{\xi}_{2t})\begin{pmatrix} \hat{p}_{11} & 1-\hat{p}_{22} \\ 1-\hat{p}_{11} & \hat{p}_{22} \end{pmatrix}\begin{pmatrix} \hat{\mu}_1 \\ \hat{\mu}_2 \end{pmatrix} \tag{1.11}$$

where $\hat{\mu}_1$ and $\hat{\mu}_2$ are the estimated mean changes in CDS spreads for state 1 and state 2, respectively. In particular, they are given by taking the expectation of the CDS change in equations (1.3) and (1.9) for the Markov switching structural model and Markov switching AR(1) model, respectively. Moreover, $\hat{\xi}_{1t}$ and $\hat{\xi}_{2t}$ are the filtered probabilities where S_t equals 1 and 2, respectively. Multiplying these filtered probabilities by the transition probability matrix will give us an estimate of the probability that states 1 and 2 will hold at time *t* + 1. In turn, multiplying these probabilities by the estimated mean change in each state will generate an expected change in the CDS spread.

5. In-sample performance of the models

Tables 2, 3 and 4 show the in-sample performance of the linear models, the Markov switching structural model and the Markov switching AR(1), respectively. For each CDS index, we report coefficient estimates (and their significance), t-statistics (in parentheses), R-squared*,* Akaike information (AIC), Schwarz (BIC) criterion values and transition probabilities of the Markov switching models. Most of the explanatory variables are highly significant for each model, in both regimes and for both indices. The structural models (both linear and non-linear) show a better in-sample performance than their respective AR(1) models in terms of both R-squared values (reported for the linear models only) and AIC/BIC values (except for the case of the *non-financials* index in which the BIC value obtained from the AR(1) model is slightly lower than that from the structural model). The probabilities of remaining in each regime are high, thus implying persistence. Figure 2 plots the filtered probabilities of being in the volatile regime for the *non-financials* (lower panel) and *financials senior* (upper panel) indices. Our sample period is clearly affected by different regimes of volatility in the CDS market. Interestingly, in the case of the *non-financials* iTraxx index, we find that the autoregressive term is not significant in the high volatility state and takes a negative sign. The outputs from the Markov switching models suggest that CDS spreads are positively autocorrelated in low volatility periods. However, when volatility is high, the autocorrelation disappears. In the period we analysed, which includes one of the worst crisis in the financial markets, the latter finding is probably due to the fact that credit investors sold off their CDS positions either to reap profits (if any) or to avoid further losses.

6. Out-of-sample statistical performance of the models

The analysis of the statistical performance of the forecasting models is based on the comparison between the point forecasts generated by each model and the actual values of the daily changes in CDS spreads. As stated in Section 2, we estimated the models over three different sample periods. This allows us to analyse three sets of daily point forecasts over three out-of-sample periods. In particular, the three out-of-sample periods are (1) from January 1, 2007 to September 15, 2010; (2) from January 1, 2008 to September 15, 2010; (3) from August 1, 2008 to September 15, 2010. In order to generate the daily forecasts, each model is estimated recursively. In particular, we fix the initial estimation date at September 22, 2005 and additional observations are added every day to the in-sample estimation period as they become available.

We employ three main indicators to evaluate the statistical performance of each model's forecasts, namely the root mean squared error (RMSE), the mean absolute error (MAE) and the mean correct prediction (MCP) of the direction of CDS spread changes. These forecasts are then compared with those obtained from the AR(1) model, which is our benchmark model. The choice of opting for the AR(1) model as our benchmark is mainly due to the fact that Byström (2006) finds that it well describes the statistical features of iTraxx CDS spreads. Subsequently, we perform both the modified Diebold and Mariano (1995) test (MDM, hereafter) and the Giacomini and White (2006)'s predictive ability test (GW, hereafter) for the RMSE and MAE indicators and a 2-proportion *z*-test for the MCP indicator.[10]. Furthermore, in order to improve the statistical comparison between linear and non-linear models we also implement the weighted modified Diebold and Mariano test (WMDM, hereafter) introduced by van Dijk and Franses (2003). These statistical tests are used to test the null hypothesis that the model under consideration and the AR(1) have equal forecasting ability.

6.1 Description of the statistical tests

We now describe the main characteristics of these two tests. As we are performing pairwise comparisons of models' forecasts, we have to define two series of forecasted changes in the iTraxx index price. The first one corresponds to the series of forecast changes generated by our benchmark model (the AR(1) model) defined as $\left(\mathrm{f}\widehat{\Delta\mathrm{CDS}}^{\mathrm{AR}}_{\mathrm{t|t-1}}\right)^{\mathrm{n}}_{\mathrm{t=1}}$. The second one is the series of forecast changes generated by model *i*, where *i* corresponds to the model under consideration, which can be any of the remaining models we estimated, namely the random walk (with no drift), the structural model, the Markov switching structural model, the Markov switching AR(1). This second series is defined as $\left(\mathrm{f}\widehat{\Delta\mathrm{CDS}}^{\mathrm{i}}_{\mathrm{t|t-1}}\right)^{\mathrm{n}}_{\mathrm{t=1}}$. The next step is to define, for each of the two series of forecast changes, a loss function, namely $\mathrm{h}\left(\mathrm{e}^{\mathrm{AR}}_{\mathrm{t}}\right)$ and $\mathrm{h}\left(\mathrm{e}^{\mathrm{i}}_{\mathrm{t}}\right)$ for the benchmark model and the *i*th model under consideration, respectively. $\left(\mathrm{e}^{\mathrm{AR}}_{\mathrm{t}}\right)^{\mathrm{n}}_{\mathrm{t=1}}$ represents the forecast errors between the benchmark model and the actual series of CDS spread changes. Similarly, $\left(\mathrm{e}^{\mathrm{i}}_{\mathrm{t}}\right)^{\mathrm{n}}_{\mathrm{t=1}}$ represents the forecast errors between the *i*th model under consideration and the actual series of CDS spread changes. Finally, a loss differential in period *t*, defined as $\mathrm{d}^{\mathrm{i}}_{\mathrm{t}} = \mathrm{h}\left(\mathrm{e}^{\mathrm{i}}_{\mathrm{t}}\right) - \mathrm{h}\left(\mathrm{e}^{\mathrm{AR}}_{\mathrm{t}}\right)$, constitutes the basis for our hypothesis testing. In particular, we test the null hypothesis (H_0) for the MDM test, defined as $\mathrm{E}\left(\mathrm{d}^{\mathrm{i}}_{\mathrm{t}}\right) = 0$, against the alternative hypothesis (H_1) that $\mathrm{E}\left(\mathrm{d}^{\mathrm{i}}_{\mathrm{t}}\right) \neq 0$. As we are performing one-step ahead forecasts, we use the test statistic suggested by Harvey et al. (1997):

$$MDM^{i} = \frac{\bar{d}^{i}}{\sqrt{\mathrm{var}\left(\bar{d}^{i}\right)}} \tag{1.12}$$

[10] It is worth mentioning that the MCP cannot be calculated for the random walk model.

where $\bar{d}^i = \frac{\sum_{t=1}^{n} d_t^i}{n}$ and $var(\bar{d}^i) = n^{-1}\left[\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right]\left[\frac{n+1-2h+n^{-1}h(h-1)}{n}\right]$. γ_0 represents the sample variance of the d_t^i series, γ_k denotes its kth autocovariance and h is the forecast horizon which is set equal to 1 in our case.

As the value of $var(\bar{d}^i)$ has to be estimated, the test statistic in (1.12) follows a *t*-distribution with $(n-1)$ degrees of freedom.

Non-linear models are more suited to predict extreme (large positive or negative) observations than linear models. van Dijk and Franses (2003) show that in order to better compare forecasts generated by linear and non-linear models, the main focus should be on the ability of each model to predict the tails of the unconditional distribution of the dependent variable, which in our case is the CDS index spread change. Hence, they suggest a modification of the MDM test in order to attribute more weight to extreme observations:

$$WMDM^i = \frac{\bar{d}_w^i}{\sqrt{\mathrm{var}(\bar{d}_w^i)}} \tag{1.13}$$

where $\bar{d}_w^i = \frac{\sum_{t=1}^{n} w(\omega_t) d_t^i}{n}$ and $\omega_t = \{\Delta CDS_{t-j},\ j = 0, 1, \ldots\} = \Phi(\Delta CDS_t)$. $var(\bar{d}_w^i)$ is computed as in equation (1.12) and $\Phi(\Delta CDS_t)$ represents the cumulative distribution function of the CDS index spread changes. This way, we want to place more weight on the observations in the right tail of the unconditional distribution of CDS changes. These observations are likely to correspond with high volatility and distress periods in the CDS market. Similar to the MDM statistics, the WMDM statistics follows a *t*-distribution with $(n-1)$ degrees of freedom.

We also conduct the GW test of conditional forecasting ability of the models. The GW test has a number of advantages over the standard conventional out-of-sample predictive ability testing. This test is notably known for its ability to adequately compare nested and non-nested models unlike many other forecast evaluation tests. It allows a unified treatment of non-nested and nested models. Furthermore, the GW test effectively deals with the fact that recursively estimated models could be polluted by problems of parameter estimation error. The GW test is conditional on the values of parameter estimates in the model. To test the null hypothesis of equal conditional predictive ability $\left(H_0 : \mathrm{E}\left[d_{t+\tau}^i \mid \Im_t\right] = 0\right)$ i.e. the two forecast models are equally accurate on average. The proposed test statistic for the GW test can be calculated as:

$$GW^i = T\left(T^{-1}\sum_{t=1}^{T-\tau}\Im_t d_{t+\tau}^i\right)'\hat{\Omega}_T^{-1}\left(T^{-1}\sum_{t=1}^{T-\tau}\Im_t d_{t+\tau}^i\right) \tag{1.14}$$

where the covariance matrix $\hat{\Omega}_T$ is a consistent HAC estimator for the asymptotic variance of $\Im_t d_{t+\tau}^i$, where $\Im_t$ is the information set available at time *t*. The test statistic follows a chi-squared distribution.

As highlighted earlier, we use a 2-proportion *z*-test to analyse the statistical performance of the models in terms of the MCP indicator. In this case, the null hypothesis to be tested is that the proportions of correctly signed forecasts of CDS changes, namely the MCP indicators, from the benchmark model and the model under consideration are identical. The alternative hypothesis is that the given pair of models produces different proportions. In order to perform the test, we calculate the following *z*-statistic:

$$z = \frac{(\hat{p}_1 - \hat{p}_2)}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}} \tag{1.15}$$

where $\hat{p}_1$ is the MCP computed for the model under consideration, $\hat{p}_2$ is the MCP computed for the benchmark model and $\hat{p}$ is the ratio between the total number of success (that is the number of correct forecasts of the direction of CDS changes) in both samples of forecasts (for the pair of models under analysis) and the total number of observations in both samples (that is $n_1 + n_2$).

6.2 Statistical predictability: results

Table 5 and Table 6 report the out-of-sample performance of the forecasting models for the *non-financials* and *financials senior* CDS indices, respectively. Both tables report the values obtained for the RMSE, MAE and MCP, which are based on forecasts produced by the random walk model (Panel A), the structural model (Panel B), the AR(1) model (Panel C), the Markov switching structural model (Panel D) and the Markov switching AR(1) model (Panel E). *, ** and *** represent rejection of the null hypothesis in favour of the alternative H_1 for the MDM test and the 2-proportion z-test at the 10%, 5% and 1% significance levels, respectively. †, †† and ††† represent rejection of the null hypothesis in favour of the alternative H_1 for the WMDM test at the 10%, 5% and 1% significance levels, respectively. Finally ^, ^^, ^^^ represent rejection of the null hypothesis in favour of the alternative H_1 for the GW test at the 10%, 5% and 1% significance levels, respectively.

For both CDS indices, the tests clearly show that, based on the RMSE and MAE metrics, the random walk and the Markov switching structural model generate forecasts which are statistically different (in most occasions at the 1% significance level) from the forecasts generated by our benchmark model, namely the AR(1) model. Interestingly, the structural model and the Markov switching AR(1) produce forecasts which are statistically equal to the AR(1) model for almost all sub-periods. Relative to the Markov switching structural model, the WMDM test does not reject the null hypothesis (except in two cases for the *non-financials* index), which is instead rejected by the MDM and GW tests. With respect to the structural model, while the MDM and WMDM tests do not reject the null at the 5% significance level, the GW test rejects H_0 at the 1% level in all cases for the RMSE indicator. In general, it seems fair to conclude that the AR(1), the Markov switching AR(1) and the structural model are superior to both the random walk and the Markov switching structural model.

Based on these metrics and statistical tests, we find that there is supporting evidence of a statistically predictable pattern in the evolution of the changes in spreads for both the *non-financials* and *financials senior* CDS indices.

7. The economic performance of the models

In the previous section, the results showed that there is some evidence of statistical predictability in the iTraxx CDS index spreads. For this reason, it is worth investigating this in more depth. In order to do that, we examine the economic significance of the models' performance by creating trading strategies based on point forecasts.

7.1 The trading rules

In order to build trading strategies based on iTraxx index CDS spreads, we follow Byström (2006) and treat the CDS index spread as a corporate bond spread. We add the index spread to the risk-free interest rate and use their sum to price a hypothetical 5-year zero coupon corporate bond with notional amount *N* (arbitrarily chosen).[11]

[11] We are aware that iTraxx indices are not traded this way in the real world. However, ours represents a simple and accurate way to quantify the magnitude of profits that can be made from trading the index. In the real world, a trader willing to buy (sell) the index would have to pay (receive) a quarterly fixed coupon in addition to upfront payments made at initiation and close of the trade (to reflect the change in price of the index). Furthermore, he would have to account for any accrued interest between the launch of the index and the trade date. In order to compute upfront payments, the price of the index at the trade date has to be determined. This is given by the par minus the present

We use the following trading rule:

If $\Delta CDS_{t-1} < (>) \ (1+\theta) \ f\widehat{\Delta CDS}^{i}_{t|t-1}$, then a trader would go short (long) a 5-year zero coupon bond; θ represents a trading trigger defined by the trader. The use of a trading trigger is introduced in order to reduce the impact of transaction costs on the overall profitability of the strategies. In fact, the use of no (or low) triggers resulted in extremely negative returns in the similar study conducted by Byström (2006).

This trading rule is based on the fact that if the forecasted change in the CDS spread is considerably higher (lower) than the current spread, then the CDS index spread is expected to increase (decrease). The latter, in turn, would induce a contemporaneous decrease (increase) in the price of the zero coupon bond. Based on this prediction, a trader would sell (buy) the bond. Following Byström (2006), we assume that all trades are made either at the bid or ask prices, in order to include transaction costs when implementing the trading rule. Specifically, we buy at the ask price and sell at the bid price.

We experiment the implementation of three different trading strategies, which are based on the same trading rule. In particular, the first strategy uses a trading trigger θ which equals 1 basis point and a holding period of one day. The second strategy explores a trading trigger θ of 2 basis points and a holding period of one day. The third strategy does not use a trading trigger ($\theta = 0$) but is characterised by a holding period of one week (5 days). The latter strategy draws on the finding of Blanco et al. (2005) about the average half-life of deviations between CDS spreads and credit spreads. They argue that spreads revert to equilibrium in approximately 6 days, on average. Even though their study is on individual credit obligors, they compute the average half-life of deviations across the pool of companies in their dataset. Our focus is on the iTraxx CDS index, which is a pool of companies with different credit risk characteristics. Hence, the comparison between our data sample and theirs is appropriate. By implementing this strategy, we then capture potential delays in the expected change in CDS spreads.

7.2 Results on the profitability of the trading strategies

In Tables 7 and 8 we report the annualised Sharpe ratios generated by the trading rules (described in the previous section), together with their respective asymptotic 95% confidence intervals (95% CI), for each strategy over the three out-of-sample periods, namely January 2006 to September 2010, January 2008 to September 2010 and August 2008 to September 2010. The number of trades and the returns (expressed in percentages) of the strategies are also reported. In particular, results are shown for both the *non-financials*

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value of the spread differences. Bloomberg provides a function, namely <CDSW>, which computes the index price for any level of spread and recovery rate assumptions.

(Table 7) and *financials senior* (Table 8) CDS indices for trading strategies based on forecasts produced by the structural model (Panel A), the AR(1) model (Panel B), the Markov switching structural model (Panel C) and the Markov switching AR(1) model (Panel D).

In the case of the *financials senior* CDS index, we notice that the Sharpe ratios are negative most of the times, except for three cases. However, for the *non-financials* iTraxx index, we observe positive Sharpe ratios more frequently. In particular, the linear AR(1) model generates positive values over every out-of-sample period for strategies which require a trading trigger (of 1 or 2 basis points) and a daily holding period. Differently, holding positions for one week would result in highly negative returns and Sharpe ratios. On the other hand, a 1-week holding period would be beneficial for the structural model as positive returns and Sharpe ratios would be gained in 2 (out of 3) out-of-sample periods. The use of a high trading trigger (2 basis points) also generates positive Sharpe ratios for the Markov switching AR(1) model in all out-of-sample periods. The Markov switching structural model generates negative Sharpe ratios in every case.

The fact that positive Sharpe ratios are found in some instances is not surprising and in line with our analysis in Section 6, where we analysed the statistical performance of the models and found that the random walk model generates worse forecasts than the AR(1), the structural model and the Markov switching AR(1) model. The trading strategies which are based on the latter models are indeed the only ones for which we observe some evidence of profitability.

8. Robustness tests

In this section, we perform two main robustness tests. First, we evaluate the predictive performance of the structural models by estimating them replacing the level and slope of the yield curve (proxied by the level and slope of swap rates) with the first two principal components retrieved by the term structure of swap rates; and second, we evaluate the statistical performance of the forecasting models (as described in Section 6) under the assumption that investors in the CDS index market have an asymmetric loss function.

As suggested by Alexander and Kaeck (2008), the first two principal components can replace the risk-free interest rate (for the level) and the difference between a 10-year rate and 2-year rate (for the slope), respectively, in the estimation of the structural models. This allows us to test whether the use of principal components shows a higher predictive power than swap rates and whether it improves the out-of-sample performance of the forecasting models.[12] To this end, we estimate the linear and Markov switching structural models described by equations (1.1) and (1.3), respectively, by replacing Δr_{t-1}^{5} and $\Delta(r_{t-1}^{10} - r_{t-1}^{2})$ with the first and second principal components. We apply a principal component analysis to the term structure of changes in swap rates with maturities from 1 year to 30 years. The statistical and economic performance of the structural models are then evaluated and shown in Table 9. Relative to the *non-financials* index, the structural model generates a slightly worse statistical performance (the null of equal predictive accuracy for the MAE indicator is rejected at the 5% level, while it was only rejected at the 10% in the case of swap rates) as well as economic performance (none of the Sharpe ratios are positive while in 2 cases positive values were found in the case of model's implementation based on swap rates). With respect to the Markov switching structural model, both the statistical and economic performances are generally similar to the results in Sections 6 and 7, with the only difference being that one positive Sharpe ratio is now found for the 1-week holding period strategy. The analysis of the *financials senior* index reveals instead that using principal components generates a similar statistical performance of the linear and non-linear structural models (compared to the implementation based on swap rates) and a slight increase in the occurrences of positive Sharpe ratios. .

The analyses we carried out in the previous sections have been based on symmetric loss functions. This implies that both positive and negative forecast errors of similar magnitude have the same loss. However, CDS investors may have asymmetric loss functions and their ability of using information for generating forecasts may not be detected by standard statistical tests if the true loss is indeed asymmetric. We follow Elliot et al. (2008) and assume the following generalized loss function:

$$h\left(\mathrm{e}_{t+1}^{i};\ \alpha; p\right) = \left[\alpha + (1-2\alpha)1_{\left(\mathrm{e}_{t+1}^{i}<0\right)}\right] |\mathrm{e}_{t+1}^{i}|^{p}, \qquad 0 < \alpha < 1 \tag{1.16}$$

where α defines the degree of asymmetry which allows different penalizations for under- and over-predictions.[13] The value of *p* helps define the overall shape of the loss function. For instance, a value of *p* equal to 1 defines a linear loss function, which combined with a value of α equal to 0.5, gives the special case of the MAE loss function. We assume two different values for α, namely 0.25 (which penalizes negative forecast errors more heavily than positive ones) and 0.75 (which puts a greater penalization on positive forecast errors). We use the loss function defined in equation (1.16) to measure the out-of-sample statistical performance of the forecasting models (described in Section 4). Results are generally in line with those reported in Table 5 and Table 6 for the *non-financials* and *financials senior* CDS indices,

[12] We would like to thank an anonymous reviewer for pointing this out.
[13] Note that a value of α of 0.5 would imply a symmetric loss function.

respectively.[14] Small differences arise in some cases. For instance, relative to the *non-financials* index, the null hypothesis is rejected more often than under the assumption of a symmetric loss for the Markov switching AR(1) model and the GW test never rejects the null for the RMSE of the structural model (whereas in the symmetric case the null is always rejected at the 1% significance level). Further, if α=0.75 the null is not rejected in a higher number of cases (than the symmetric case) for the Markov switching structural model. The same pattern is observable for the *financials senior* index.

9. Conclusion

Previous studies on the CDS market have predominantly focused on determining the economic factors that influence CDS spreads. To our knowledge, none of these studies have examined whether future CDS spreads are predictable using these economic determinants. This study aims to bridge that gap in the literature. Our paper is novel as it is the first paper to investigate whether it is possible to forecast CDS spreads using advanced econometric models. It is also the first study to evaluate trading strategies for CDS spreads using forecasts from robust econometric models.

We consider the most liquid CDS market in Europe, namely the iTraxx CDS index and focus on the *non-financials* and *financials senior* iTraxx indices. We employ both linear and non-linear forecasting models. For the linear forecasting models, we use a structural model and an AR(1) model, whereas for non-linear models we consider the Markov switching structural model and the Markov switching AR(1) model. Point forecasts from each model are generated and their statistical and economic performances are assessed. Specifically, the statistical performances of the models are evaluated via the use of statistical metrics (RMSE, MAE and MCP), while their economic performance is tested by implementing trading strategies based on iTraxx CDS spreads. We find that the statistical analysis of the models is generally coherent with their trading results. In fact, the models which perform better from a statistical viewpoint - the structural model, the AR(1) model and the Markov switching AR(1) model - are also the models that generate positive returns and Sharpe ratios in some instances. Implementing the linear and non-linear structural models with principal components (rather than swap rates) yields slightly higher Sharpe ratios for the *financials senior* index (for both the linear and non-linear structural models). Overall, we find that linear models often outperform Markov switching models. Markov switching models, instead, provide a good in-sample fit for iTraxx index data. Another interesting finding relates to the existence of first-order autocorrelation in iTraxx Europe spreads. In low-volatility regimes, we find positive autocorrelation in

[14] Results on the statistical performance of the models under the assumption of an asymmetric loss function are available on request.

CDS spreads, in line with previous studies which analysed the iTraxx index. However, in high-volatility states, the autocorrelation coefficient becomes insignificant and this may be explained by the jittery reaction of credit investors who had been selling off their CDS positions while the financial crisis was sluggishly unfolding. In conclusion, our findings show some evidence of predictability for the most liquid CDS index in Europe. As a result, the iTraxx index cannot be regarded as informationally efficient in its weak form altogether, and hence trading the index should be incentivised based on speculative reasons. In other words, trading the index could be profitable for an investor who is eager to exploit market inefficiencies.

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Table 1 – Summary statistics

This table reports the summary statistics for the changes in the variables used in our analysis over the whole sample period. The CDS spreads for *financials senior* (CDS_{fin}) and *non-financials* (CDS_{nofin}) represent our dependent variables. The independent variables are the equally weighted portfolio of stocks comprising the same members of the CDS indices ($Equity_{fin}$ and $Equity_{nofin}$, respectively for the *financials senior* and *non-financials* sub-indices), the level of the risk-free interest rate (r_5), the slope of the yield curve ($r_{10} - r_2$), the VStoxx implied volatility index (V).

	Mean	Std dev	Skewness	Kurtosis	Bera-Jarque	ρ_1	ADF
CDS_{fin}	0.1017	4.9137	-0.4666	18.1176	13678.71***	0.127***	-22.5877***
CDS_{nofin}	0.0498	4.9078	6.8367	149.9050	1024912***	-0.042	-9.5454***
$Equity_{fin}$	0.0002	0.0227	0.2790	12.6447	5564.893***	0.052*	-9.2523***
$Equity_{nofin}$	0.0008	0.0183	1.4473	48.4918	97833.63***	0.006	-21.2677***
r_5	0.0000	0.0005	0.0512	4.7944	192.6095***	-0.029	-38.9321***
$r_{10} - r_2$	0.0000	0.0003	-0.1667	8.5259	1827.321***	0.094***	-8.2833***
V	0.0039	2.0699	1.8298	29.0801	41353.68***	-0.041	-11.8205***

*, **, *** denote rejection of the null hypothesis at the 10%, 5%, 1%, respectively.

Table 2 - Parameter estimates for Structural Model and AR(1)

Estimated parameters, over the whole sample, for the OLS regressions of changes in European iTraxx CDS indices on lagged theoretical determinants of CDS spreads (as defined in equation 1.1) and on lagged CDS spreads (as defined in equation 1.2) are shown in Panel A and B, respectively. Standard t-statistics are given within brackets. We also report R^2, Akaike information (AIC) and Schwarz (BIC) criterion values.

$Const.$	ΔCDS_{t-1}	$EQUITY\_R_{t-1}$	Δr^{5}_{t-1}	$\Delta(r^{10}_{t-1} - r^{2}_{t-1})$	ΔV_{t-1}	R^2	AIC/BIC
Panel A: Structural Model							
Non-financials							
0.069	-0.073**	-19.984**	-1.319	-8.794**	0.022	0.013	6.018/6.045
(0.472)	(-2.247)	(-2.041)	(-0.428)	(-2.265)	(0.266)		
Financials senior							
0.073	0.140***	-9.723	-10.653***	0.051	-0.389***	0.043	5.977/6.002
(0.532)	(3.966)	(-1.165)	(-3.433)	(0.012)	(-4.717)		
Panel B: AR(1)							
Non-financials							
0.050	-0.042	-	-	-	-	0.002	6.022/6.031
(0.340)	(-1.423)						
Financials senior							
0.076	0.123***	-	-	-	-	0.015	5.999/6.007
(0.550)	(4.361)						

*, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1%, respectively.

Table 3 – Parameter estimates for Markov Switching Structural Model

Estimated parameters, over the whole sample, for the Markov switching regressions of changes in European iTraxx CDS indices on lagged theoretical determinants of CDS spreads (as defined in equation 1.3). Standard t-statistics are given within parentheses. We also report the transition probabilities (p_{ij}), Akaike information (AIC) and Schwarz (BIC) criterion values.

	$Const.$	ΔCDS_{t-1}	$EQUITY\_R_{t-1}$	Δr^5_{t-1}	$\Delta(r^{10}_{t-1} - r^2_{t-1})$	ΔV_{t-1}	p_{ij}	AIC/BIC
Non-financials								
Regime 1	0.053	0.078***	-18.06***	-4.764***	2.073	0.380***	0.95	5.493/5.560
	(1.426)	(3.734)	(-5.816)	(-5.579)	(1.562)	(10.749)		
Regime 2	0.105	-0.070	-61.29***	-14.495**	-2.600	0.654***	0.92	
	(0.341)	(-1.517)	(-3.412)	(-2.313)	(-0.348)	(4.781)		
Financials senior								
Regime 1	-0.016	0.269***	-3.384**	-0.401	-0.067	0.050***	0.99	5.728/5.790
	(-1.506)	(5.182)	(-2.313)	(-1.285)	(-0.118)	(2.872)		
Regime 2	0.058	0.081***	-102.6***	-17.476***	-10.952**	0.256***	0.99	
	(0.316)	(2.923)	(-13.299)	(-5.155)	(-2.542)	(3.081)		

*, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1%, respectively.

Table 4 – Parameter estimates for Markov Switching AR(1)

Estimated parameters, over the whole sample, for the Markov switching regressions of changes in European iTraxx CDS indices on lagged CDS spreads (as defined in equation 1.9). Standard t-statistics are given within brackets. We also report the transition probabilities (p_{ij}), Akaike information (AIC) and Schwarz (BIC) criterion values.

	$Const.$	ΔCDS_{t-1}	p_{ij}	AIC/BIC
Non-financials				
Regime 1	0.0283	0.1525***	0.98	5.947/5.978
	(0.204)	(5.117)		
Regime 2	-0.0167	-0.581	0.98	
	(-0.423)	(1.000)		
Financials senior				
Regime 1	0.077	0.258***	0.99	5.943/5.972
	(0.432)	(2.830)		
Regime 2	-0.071	0.162***	0.99	
	(-0.231)	(4.211)		

*, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1%, respectively.

Table 5 – Out-of-sample performance of the forecasting models for the *non-financials* CDS index

This table presents the out-of-sample performance of each model for the *non-financials* CDS index. We report the root mean squared error (RMSE), the mean absolute error (MAE) and the mean correct prediction (MCP) of the sign of the CDS spread change. We generated forecasts by implementing the random walk model (Panel A), the structural model (Panel B), the AR(1) model (Panel C), the Markov switching structural model (Panel D) and the Markov switching AR(1) model (Panel E). To test the null hypothesis that the AR(1) model and the model under consideration generate equal forecasts, we perform the MDM, the WMDM and the GW tests (for RMSE and MAE) and the 2-proportion *z*-test (for MCP). We estimated the models recursively for three different sample periods: January 2007 to September 15, 2010; January 2008 to September 15, 2010 and August 2008 to September 15, 2010.

	Jan 2007 – Sep 2010	Jan 2008 – Sep 2010	Aug 2008 – Sep 2010
Panel A: Random Walk (with no drift)			
RMSE	$8.24^{***\wedge\wedge\wedge}$	$9.49^{***\wedge\wedge\wedge}$	$9.18^{***\wedge}$
MAE	$4.17^{***\wedge\wedge\wedge}$	$5.14^{***\wedge\wedge\wedge}$	$4.88^{***\wedge\wedge\wedge}$
Panel B: Structural Model			
RMSE	$5.74^{*\wedge\wedge\wedge}$	$6.59^{*\wedge\wedge\wedge}$	$6.49^{*\wedge\wedge\wedge}$
MAE	2.95^{*}	3.60^{*}	3.43^{*}
MCP (%)	48.14	48.76	48.69
Panel C: AR(1)			
RMSE	5.72	6.57	6.46
MAE	2.92	3.56	3.39
MCP (%)	47.54	47.94	48.29
Panel D: Markov Switching Structural Model			
RMSE	$5.85^{***\dagger\dagger\wedge\wedge\wedge}$	$6.63^{***\wedge\wedge\wedge}$	$6.52^{***\wedge\wedge\wedge}$
MAE	$3.06^{***\dagger\dagger\dagger\wedge\wedge\wedge}$	$3.68^{***\wedge\wedge\wedge}$	$3.50^{***\wedge\wedge}$
MCP (%)	47.90	48.43	48.69
Panel E: Markov Switching AR(1)			
RMSE	5.72	6.56	6.45
MAE	$2.93^{\dagger\dagger\dagger}$	3.57	3.39
MCP (%)	48.62	48.27	48.69

*, **, *** denote rejection of the null hypothesis test of the MDM test at the 10%, 5% and 1%, respectively. †, ††, ††† denote rejection of the null hypothesis test of the WMDM test at the 10%, 5% and 1%, respectively. ^, ^^, ^^^ denote rejection of the null hypothesis test of the GW test at the 10%, 5% and 1%, respectively.

Table 6 – Out-of-sample performance of the forecasting models for the *financials senior* CDS index

This table presents the out-of-sample performance of each model for the *financials senior* CDS index. We report the root mean squared error (RMSE), the mean absolute error (MAE) and the mean correct prediction (MCP) of the sign of the CDS spread change. We generated forecasts by implementing the random walk model (Panel A), the structural model (Panel B), the AR(1) model (Panel C), the Markov switching structural model (Panel D) and the Markov switching AR(1) model (Panel E). To test the null hypothesis that the AR(1) model and the model under consideration generate equal forecasts, we perform the MDM, the WMDM and the GW tests (for RMSE and MAE) and the 2-proportion *z*-test (for MCP). We estimated the models recursively for three different sample periods: January 2007 to September 15, 2010; January 2008 to September 15, 2010 and August 2008 to September 15, 2010.

	Jan 2007 – Sep 2010	Jan 2008 – Sep 2010	Aug 2008 – Sep 2010
Panel A: Random Walk (with no drift)			
RMSE	7.50***^^^	8.52***^^^	8.33***^^^
MAE	4.72***^^^	5.82***^^^	5.66***^^
Panel B: Structural Model			
RMSE	5.79^^^	6.53^^^	6.50^^^
MAE	3.60	4.42	4.31
MCP (%)	51.80	50.82	51.53
Panel C: AR(1)			
RMSE	5.79	6.54	6.53
MAE	3.59	4.40	4.33
MCP (%)	50.38	49.03	47.90
Panel D: Markov Switching Structural Model			
RMSE	6.22***	6.67***^^^	6.63^^^
MAE	3.75***^^	4.51***^	4.38
MCP (%)	50.60	49.63	50.00
Panel E: Markov Switching AR(1)			
RMSE	5.96	6.55^^	6.54
MAE	3.62	4.41	4.33
MCP (%)	49.84	48.73	47.90

*, **, *** denote rejection of the null hypothesis test of the MDM test at the 10%, 5% and 1%, respectively. †, ††, ††† denote rejection of the null hypothesis test of the WMDM test at the 10%, 5% and 1%, respectively. ^, ^^, ^^^ denote rejection of the null hypothesis test of the GW test at the 10%, 5% and 1%, respectively.

Table 7 – Profitability of trading strategies based on the models' forecasts for the *non-financials* index

We implement trading strategies on the *non-financials* CDS index, which are based on point forecasts obtained from the structural model (Panel A), the AR(1) model (Panel B), the Markov switching structural model (Panel C) and the Markov switching AR(1) model (Panel D). For each strategy, we report the number of trades, the returns over the out-of-sample period and the annualised Sharpe ratio together with its 95% confidence interval (95% CI) in parentheses based on the asymptotic distribution valid for non-iid returns derived in Opdyke (2007).

Threshold	Jan 2007 – Sep 2010			Jan 2008 – Sep 2010			Aug 2008 – Sep 2010		
	Trades	Return (%)	Sharpe	Trades	Return (%)	Sharpe	Trades	Return (%)	Sharpe
Panel A: Structural Model									
+/- 1bp	76	9.52	-0.12	71	5.31	-0.13	57	2.07	-0.39
95% CI			(-0.21, -0.04)			(-0.23, -0.03)			(-0.56, -0.22)
+/- 2bp	13	9.96	-0.12	11	5.79	-0.10	8	3.62	-0.10
95% CI			(-0.21, -0.03)			(-0.20, -0.01)			(-0.20, 0.00)
Hold 1week	183	-0.18	-0.23	134	4.25	0.62	105	6.18	1.27
95% CI			(-0.39, -0.07)			(0.37, 0.86)			(0.85, 1.70)
Panel B: AR(1)									
+/- 1bp	20	12.23	0.43	15	7.92	0.55	6	4.83	0.47
95% CI			(0.26, 0.60)			(0.31, 0.78)			(0.16, 0.78)
+/- 2bp	6	11.46	0.38	4	7.23	0.54	1	5.17	0.71
95% CI			(0.13, 0.62)			(0.12, 0.97)			(0.11, 1.32)
Hold 1week	183	-21.05	-3.40	134	-22.86	-5.31	105	-20.20	-5.67
95% CI			(-4.15, -2.66)			(-6.26, -4.37)			(-6.87, -4.46)
Panel C: Markov Switching Structural Model									
+/- 1bp	118	4.60	-0.70	107	0.07	-0.90	86	-2.16	-1.11
95% CI			(-0.88, -0.51)			(-1.14, -0.65)			(-1.43, -0.79)
+/- 2bp	38	6.96	-0.74	31	2.65	-0.93	21	0.97	-0.92
95% CI			(-1.05, -0.44)			(-1.34, -0.53)			(-1.34, -0.49)
Hold 1week	183	-7.91	-1.30	134	-4.91	-1.12	105	-5.62	-1.47
95% CI			(-1.59, -1.01)			(-1.35, -0.89)			(-1.80, -1.14)
Panel D: Markov Switching AR(1)									
+/- 1bp	28	6.27	-1.03	24	2.54	-1.10	14	1.98	-0.76
95% CI			(-1.46, -0.60)			(-1.58, -0.61)			(-1.20, -0.32)
+/- 2bp	8	10.55	0.03	6	6.48	0.15	2	5.02	0.62
95% CI			(-0.03, 0.09)			(0.06, 0.23)			(0.11, 1.14)
Hold 1week	183	-15.04	-2.38	134	-13.63	-2.98	105	-16.82	-4.56
95% CI			(-2.91, -1.86)			(-3.67, -2.30)			(-5.83, -3.29)

Table 8 – Profitability of trading strategies based on the models' forecasts for the *financials senior* index

We implement trading strategies on the *financials senior* CDS index, which are based on point forecasts obtained from the structural model (Panel A), the AR(1) model (Panel B), the Markov switching structural model (Panel C) and the Markov switching AR(1) model (Panel D). For each strategy, we report the number of trades, the returns over the out-of-sample period and the annualised Sharpe ratio together with its 95% confidence interval (95% CI) in parentheses based on the asymptotic distribution valid for non-iid returns derived in Opdyke (2007).

Threshold	Jan 2007 – Sep 2010			Jan 2008 – Sep 2010			Aug 2008 – Sep 2010		
	Trades	Return (%)	Sharpe	Trades	Return (%)	Sharpe	Trades	Return (%)	Sharpe
Panel A: Structural Model									
+/- 1bp	171	7.67	-0.52	159	3.76	-0.55	111	4.47	-0.23
95% CI			(-0.63, -0.41)			(-0.67, -0.43)			(-0.32, -0.14)
+/- 2bp	48	11.23	-0.33	45	7.19	-0.28	37	6.89	0.15
95% CI			(-0.45, -0.21)			(-0.39, -0.18)			(0.01, 0.30)
Hold 1week	183	3.89	0.21	134	-9.30	-1.72	105	-9.44	-2.14
95% CI			(0.08, 0.37)			(-2.01, -1.42)			(-2.57, -1.71)
Panel B: AR(1)									
+/- 1bp	90	9.62	-0.41	84	5.10	-0.48	72	2.93	-0.50
95% CI			(-0.51, -0.31)			(-0.60, -0.35)			(-0.63, -0.36)
+/- 2bp	16	10.50	-0.46	13	6.49	-0.44	10	5.20	-0.21
95% CI			(-0.66, -0.27)			(-0.63, -0.24)			(-0.31, -0.11)
Hold 1week	183	2.66	0.06	134	1.06	-0.04	105	-0.96	-0.36
95% CI			(-0.07, 0.22)			(-0.21, 0.13)			(-0.54, -0.19)
Panel C: Markov Switching Structural Model									
+/- 1bp	255	-0.41	-1.10	213	-0.14	-0.87	140	0.83	-0.69
95% CI			(-1.27, -0.93)			(-1.02, -0.72)			(-0.84, -0.54)
+/- 2bp	97	7.31	-0.70	83	4.54	-0.59	51	4.67	-0.27
95% CI			(-0.88, -0.51)			(-0.76, -0.43)			(-0.37, -0.17)
Hold 1week	183	-1.83	-0.52	134	-11.55	-2.11	105	-9.53	-2.16
95% CI			(-0.66, -0.35)			(-2.47, -1.76)			(-2.59, -1.73)
Panel D: Markov Switching AR(1)									
+/- 1bp	105	7.10	-0.65	92	3.83	-0.62	79	0.24	-0.89
95% CI			(-0.80, -0.50)			(-0.78, -0.47)			(-1.13, -0.66)
+/- 2bp	21	9.39	-0.62	15	5.75	-0.57	12	3.67	-0.52
95% CI			(-0.87, -0.36)			(-0.82, -0.32)			(-0.76, -0.29)
Hold 1week	183	0.10	-0.27	134	-6.34	-1.22	105	-4.58	-1.10
95% CI			(-0.41, -0.10)			(-1.45, -0.99)			(-1.34, -0.85)

Table 9 – Out-of-sample performance of the structural models implemented with principal components rather than swap rates

This table presents the out-of-sample performance of both the structural model and the Markov switching structural model for the *non-financials* and *financials senior* CDS index. The statistical performance is shown in Panel A. To test the null hypothesis that the AR(1) model and the model under consideration generate equal forecasts, we perform the MDM, the WMDM and the GW tests (for RMSE and MAE) and the 2-proportion *z*-test (for MCP). We estimated the models recursively for three different sample periods: January 2007 to September 15, 2010; January 2008 to September 15, 2010 and August 2008 to September 15, 2010. The economic performance is reported in Panel B, where, for each trading strategy, we report the number of trades, the returns over the out-of-sample period and the annualised Sharpe ratio together with its 95% confidence interval (95% CI) in parentheses based on the asymptotic distribution valid for non-iid returns derived in Opdyke (2007).

	Jan 2007 – Sep 2010			Jan 2008 – Sep 2010			Aug 2008 – Sep 2010		
Panel A: Statistical performance									
Non-financials:									
Structural Model:									
RMSE		$5.76^{*\wedge\wedge\wedge}$			$6.61^{*\wedge\wedge\wedge}$			$6.50^{*\wedge\wedge\wedge}$	
MAE		2.97^{**}			3.62^{**}			3.44^{*}	
MCP (%)		47.36			47.86			47.19	
Markov Switching Structural Model:									
RMSE		$5.88^{***\dagger\dagger\wedge\wedge}$			$6.66^{***\wedge\wedge\wedge}$			$6.55^{***\wedge\wedge\wedge}$	
MAE		$3.05^{***\dagger\dagger\dagger\wedge\wedge}$			$3.68^{***\wedge\wedge}$			3.50^{**}	
MCP (%)		47.24			47.45			46.68	
Financials senior:									
Structural Model:									
RMSE		$5.80^{\wedge\wedge\wedge}$			$6.55^{\wedge\wedge\wedge}$			$6.54^{\wedge\wedge\wedge}$	
MAE		3.61			4.43			4.34	
MCP (%)		51.42			50.30			49.71	
Markov Switching Structural Model:									
RMSE		$5.92^{**\wedge\wedge\wedge}$			$6.63^{**\wedge\wedge\wedge}$			$6.60^{\wedge\wedge\wedge}$	
MAE		$3.66^{**\wedge}$			$4.48^{**\wedge}$			4.38	
MCP (%)		50.22			49.93			49.43	
Panel B: Economic performance									
	Trades	Return (%)	Sharpe	Trades	Return (%)	Sharpe	Trades	Return (%)	Sharpe
Non-financials:									
Structural Model:									
+/- 1bp	73	9.99	-0.07	68	5.76	-0.06	54	2.55	-0.35
95% CI			(-0.14, 0.01)			(-0.15, 0.02)			(-0.50, -0.20)
+/- 2bp	23	8.52	-0.46	21	4.40	-0.51	14	1.97	-0.66
95% CI			(-0.69, -0.22)			(-0.78, -0.23)			(-1.04, -0.29)
Hold 1week	183	-0.22	-0.24	134	-3.99	-0.94	105	-3.78	-1.02
95% CI			(-0.38, -0.09)			(-1.16, -0.72)			(-1.27, -0.77)
Markov Switching Structural Model:									
+/- 1bp	131	3.40	-0.89	119	-0.40	-1.02	101	-0.87	-0.86
95% CI			(-1.13, -0.65)			(-1.30, -0.74)			(-1.12, -0.60)

+/- 2bp	36	6.85	-0.83	31	2.78	-0.96	25	0.70	-1.05
95% CI			(-1.22, -0.44)			(-1.43, -0.49)			(-1.59, -0.52)
Hold 1week	183	9.53	1.00	134	-4.37	-1.01	105	-7.00	-1.82
95% CI			(0.68, 1.32)			(-1.24, -0.79)			(-2.22, -1.42)
Financials senior:									
Structural Model:									
+/- 1bp	174	12.47	-0.10	163	7.57	-0.13	128	5.64	-0.06
95% CI			(-0.16, -0.03)			(-0.20, -0.05)			(-0.14, 0.02)
+/- 2bp	52	16.05	0.27	49	11.84	0.42	41	9.40	0.58
95% CI			(0.14, 0.39)			(0.24, 0.60)			(0.31, 0.86)
Hold 1week	183	5.53	0.41	134	-3.89	-0.82	105	-4.88	-1.16
95% CI			(0.25, 0.57)			(-1.00, -0.63)			(-1.42, -0.90)
Markov Switching Structural Model:									
+/- 1bp	233	4.88	-0.71	204	2.73	-0.62	144	4.88	-0.16
95% CI			(-0.83, -0.58)			(-0.74, -0.50)			(-0.24, -0.08)
+/- 2bp	74	14.09	0.04	65	9.49	0.08	49	5.67	-0.07
95% CI			(-0.03, 0.11)			(-0.00, 0.17)			(-0.15, 0.01)
Hold 1week	183	7.00	0.61	134	-5.30	-1.05	105	-9.83	-2.23
95% CI			(0.44, 0.77)			(-1.25, -0.84)			(-2.67, -1.78)

*, **, *** denote rejection of the null hypothesis test of the MDM test at the 10%, 5% and 1%, respectively. †, ††, ††† denote rejection of the null hypothesis test of the WMDM test at the 10%, 5% and 1%, respectively. ^, ^^, ^^^ denote rejection of the null hypothesis test of the GW test at the 10%, 5% and 1%, respectively.

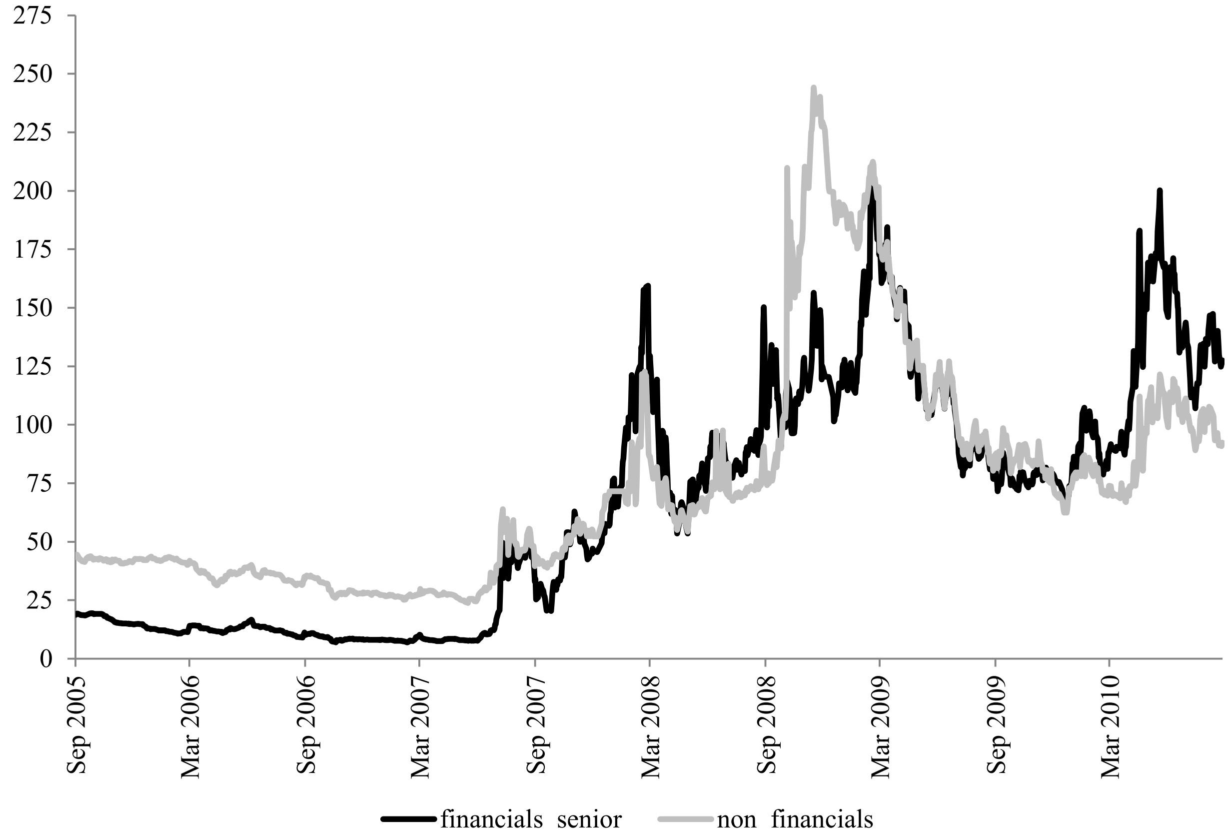

Figure 1 – Time series of CDS index spreads for *non-financials* and *financials senior*

This figure shows time series of daily CDS index spreads for both *non-financials* and *financials senior* over the period September 2005 to September 2010.

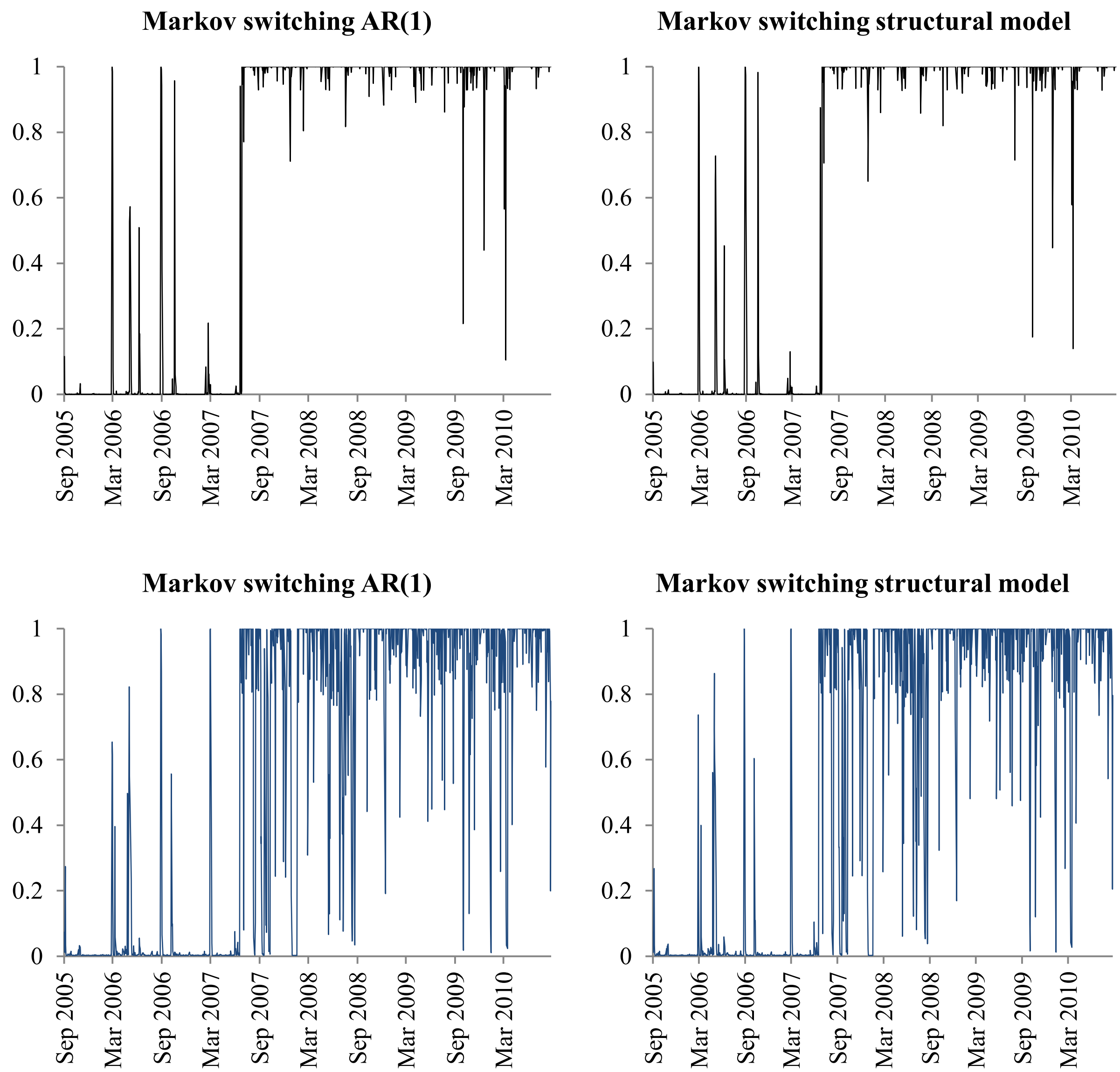

Figure 2 – Time series of regime probabilities for *financials senior and non-financials* CDS indices

This figure shows the filtered probability of being in the volatile regime estimated from both a Markov switching AR(1) model and a Markov switching structural model for the *financials senior* CDS index (upper panel in black) and the *non-financials* CDS index (lower panel in blue).