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Regime dependent determinants of credit default swap spreads ☆

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Abstract

Credit default swap (CDS) spreads display pronounced regime specific behaviour. A Markov switching model of the determinants of changes in the iTraxx Europe indices demonstrates that they are extremely sensitive to stock volatility during periods of CDS market turbulence. But in ordinary market circumstances CDS spreads are more sensitive to stock returns than they are to stock volatility. Equity hedge ratios are three or four times larger during the turbulent period, which explains why previous research on single-regime models finds stock positions to be ineffective hedges for default swaps. Interest rate movements do not affect the financial sector iTraxx indices and they only have a significant effect on the other indices when the spreads are not excessively volatile. Raising interest rates may decrease the probability of credit spreads entering a volatile period.
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1. Introduction

The trading volume on credit default swap (CDS) indices has increased tremendously during the last years. By 2006, the annual trading volume in global CDS index markets was approximately $6 trillion, representing nearly one-third of the total credit derivatives markets worldwide.[1] A contract on a CDS index provides credit protection on the pool of names in the index. CDS index contracts are very similar to single-name contracts, however a credit event of a CDS index member does not lead to the termination of the whole contract. Instead the respective entity is removed from the index and the contract continues until expiry with a reduced nominal amount. This compares with a basket credit default swap (or first-to-default swap) which also provides credit protection on a basket of entities but terminates once the first reference entity in the pool defaults. A growing number of investors are preferring to trade CDS indices rather than basket credit default swaps. Applications include credit risk hedging and relative value trading of index versus single-name investments.

In June 2004, the iBoxx and Trac-x CDS indices merged to form the Dow Jones iTraxx index family. The iTraxx CDS index family consists of the most liquid single-name CDSs in the European and Asian markets. The Europe index series is equally weighted, contains 125 single firm investment grade CDSs and is divided into the sub-indices non-financials, financials senior and financials subordinate.[2] Additionally a high volatility index is built from 30

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[1] According to the Credit Derivative Report of the British Bankers' Association (Barrett and Ewan, 2006).

[2] The non-financials index itself is subdivided into automobiles, consumers, energy, industrials, and telecom, media, and technology (TMT).

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firms with the widest CDS spread. Every six months a new series for each index is introduced in which defaulted, merged, sector changed or downgraded entities are replaced by the next most liquid ones. The exact rebalancing rules are freely available on the homepage of the International Index Company Ltd.[3], which manages the iTraxx indices: they are still traded over-the-counter (OTC). Most iTraxx CDS index products are currently traded for maturities of 3, 5, 7 and 10 years, the 5 and 10 year maturities being the most liquid.

The rapid development of the CDS market also led to growing interest in derivative products on CDSs. During 2005 JPMorgan traded about 1 billion Euros in notional per week on the OTC credit option market and since then the trading volume has been steadily increasing.[4] Many major banks have also been entering OTC trades on CDS index options during the last few years. Their clients include hedge funds, proprietary trading desks, insurance companies, investment managers and CDS index traders who use options for risk management of their positions. In March 2007 Eurex, the world's largest derivative exchange, launched exchange traded iTraxx index futures and will soon introduce other credit derivative products on iTraxx indices.

Understanding the determinants of credit spreads is important for financial analysts, traders and economic policy makers. Consequently, over the last few years a large body of academic research has used corporate bond prices or single name CDS spreads to determine the drivers of movements in credit spreads. But single name CDS spreads are much less liquid than the iTraxx indices and the credit spreads that are inferred from corporate bond prices are affected by tax considerations as well as illiquidity.

From an academic viewpoint the main attraction of iTraxx indices is that they provide liquid market prices of credit spreads of different maturities and in different economic sectors. Yet CDS indices have hardly attracted any attention in academic research. To our knowledge there are only two important empirical studies on the behaviour of CDS indices, both from Byström. Byström (2005) examines the relationship between index spread changes and stock returns and finds that the stock market tends to lead the CDS index market. Furthermore, he finds a significant positive autocorrelation in daily changes of iTraxx indices. Byström (2006) compares market prices of iTraxx indices with theoretical prices of a structural credit risk model and examines whether the detected autocorrelation might be exploited by simple trading strategies.

This paper extends Byström (2005) by examining the empirical influence of a wider set of theoretical determinants of CDS spreads on the daily changes in iTraxx Europe. We find that most theoretical variables do contribute to the explanation of CDS spread changes but that their influence depends on the prevailing market circumstances. Previous research (e.g. Yu, 2005) indicates that single-name CDS spreads may behave quite differently during volatile CDS periods compared with their behaviour in tranquil periods. We therefore apply a Markov switching model to investigate the possibility that determinants of credit spreads are regime specific and find strong evidence in favour of this hypothesis. During the volatile CDS regime credit spreads are highly sensitive to stock market variables. However, interest rates are more significant determinants of credit spreads during the (predominant) regime when CDS are less volatile. We conclude that for the efficient hedging of CDS exposures traders should adjust equity hedge ratios to the relevant regime. We also find that interest rate policy can influence the probability of entering the turbulent regime but, once there, interest rate policy will have little effect on CDS spreads. To our knowledge this paper is the first to use CDS indices in an empirical exploration of the determinants of credit spreads. It is also the first paper to provide evidence of the dependence of credit spread behaviour on the market regime. Other empirical insights to the dynamics of CDS indices include strong evidence of both positive autocorrelation and volatility clustering.

The reminder of this paper is structured as follows: Section 2 discusses on the determinants of CDS spreads. Section 3 describes the proxies for the determinants and we estimate a linear regression model in Section 4. Section 5 provides a brief introduction to Markov switching models. We apply it to our data set in Section 6. Section 7 investigates whether there is any observable variable driving regime switches and we conclude in Section 8.

2. Determinants of CDS spreads

Reduced form models of credit risk treat default as an unpredictable event. Default is the outcome of a random jump process and the reason for default is not specified.[5] By contrast, the dependence on fundamentals equips the structural approach with a wide set of empirically testable determinants of default. In structural credit risk models (for instance Merton, 1974; Black and Cox, 1976; Longstaff and Schwartz, 1995; or Zhou, 2001) default is triggered when the firm value falls below a certain threshold, which is commonly modelled as an increasing function of firm leverage. Also, assuming a particular stochastic process for the firm value allows risk neutral valuation to be used for pricing credit risk sensitive instruments.

Variables influencing CDS spreads in structural default models are now discussed. An increase in the riskfree interest rate should decrease the default probability. The theoretical argument supporting this is that this rate influences the risk neutral drift in the firm value process:

[3] www.itraxx.com.

[4] See Woolcott (2005).

[5] Among these models see: Jarrow and Turnbull (1995), Jarrow et al. (1997), and Duffie and Singleton (1999).

a higher riskfree interest rate raises the risk neutral drift and lowers the probability of default. But although there is often only one interest rate appearing in structural models, the future movement of this rate is also influenced by the slope of the yield curve. The steeper the yield curve, the higher expected future interest rates and thus we expect a negative relationship between both the riskfree interest rate and the slope of the yield curve and the CDS spread. There are further arguments to support negative relationships between these interest rate variables and CDS spreads. Low interest rates are often observed during periods of recession and frequent corporate defaults. In addition the steepness of the yield curve is an indicator of an increase in future economic activity. This is empirically supported by Fama (1984) and Estrella and Hardouvelis (1991) among others.

We now consider the effect of firm value on CDS spreads. When the market value of the firm decreases, the probability of default will increase because hitting the default barrier becomes more likely. However, the firm value is unobservable and we cannot measure its changes directly. Since changes in the firm value are induced by changes in the firm's equity value, structural models suggest that downward trends in the equity level are accompanied by upward trends in the CDS spread level. A further theoretical determinant of CDS spreads is firm value volatility. It is intuitive that hitting a default barrier becomes more likely if the firm value itself fluctuates widely. But volatility is also an unobservable variable and here we face the additional problem of being unable to observe the underlying process. However the positive relationship between the volatility of the firm value and equity volatility can be exploited. Whenever equity volatility increases, firm value volatility is expected to increase also and this should lead to an upward trend in the CDS spread.

Empirical research investigating the influence of these variables on single-name CDS include Benkert (2004), who concentrates on the influence of different volatility measures on CDS premia, finding that option implied volatility has the strongest effect; Ericsson et al. (2004) investigate the influence of leverage, volatility and interest rates on single-firm CDS concluding that all variables are important determinants of CDS spreads. Cossin et al. (2002) argue that rating is the most important single source of information in the spread. Hull et al. (2004) find evidence that CDS spreads predict negative rating events.[6]

Many of the aforementioned works have been inspired by Collin-Dufresne et al. (2001), who examined the influence of theoretical determinants of credit risk on bond spreads. But with the rapid development of the credit derivative market the empirical literature on credit risk has concentrated more on CDS spreads as a measure of credit risk: Longstaff et al. (2005) discover that whilst most of the bond spread is attributed to default risk, a significant part is due to illiquidity; Elton et al. (2001) find that the different tax treatments of corporate and government bonds have a greater effect on bond spreads than default risk; and Blanco et al. (2005) show that new information is incorporated into CDS spreads faster than into bonds and that CDS spreads are more sensitive to firm specific factors than bond spreads. Additionally, the 'price' of a CDS is usually quoted as a constant maturity spread, whereas bond spreads are calculated by subtracting an unknown risk-free interest rate from the bond yield and are not directly comparable when maturities of the underlying bonds differ.

In this paper, we also examine the effect of lagged changes in the CDS indices. Although the inclusion of lagged changes in CDS spreads is not motivated by theoretical arguments it is econometrically warranted by the findings of Byström (2005, 2006). He finds that iTraxx Europe indices show a significant autocorrelation in their spread changes so we capture this effect using lagged changes in CDS spreads as an additional explanatory variable. This also allows one to gain further insights into the significance of autocorrelation in iTraxx markets.

3. Data

We use daily quotes of iTraxx Europe CDS indices and restrict our analysis to indices with a maturity of 5 years, since they contain the most liquid CDSs. The data period starts from the beginning of iTraxx indices in June 2004 and ends in June 2007.[7] The dataset therefore covers 750 quotes for each of five indices. As mentioned above a new series for each iTraxx index is launched every six months, to adjust the membership of the index. In particular defaulted and low-liquidity entities are replaced by the most liquid entities not currently in the index. Once initiated a particular series remains static throughout its lifetime except that defaulted entities are removed. In order to ensure that our analysis is always built on the most liquid names, for every index we construct time series that contain the most recent series at any point in time.

As a proxy for risk-free interest rates in the Euro zone we use Euro swap rates with maturities between one and thirty years. Swap rates are often regarded as a better proxy for the unobservable risk-free interest rates than government bond yields (see Houweling and Vorst, 2005). Although swap rates are not totally risk-free they have the advantage of high liquidity and no-short sale

[6] Additionally Houweling and Vorst (2005) compare market prices of credit default swaps with model prices finding that a simple reduced form model prices credit default swaps better than comparing bonds yield spreads to CDS premiums.

[7] The analysis in the accepted version of this paper covered a sample that ended just before credit spreads soared during the crisis precipitated by sub-prime mortgages in the US (see Fig. 1). We have since analysed an extended sample up to September 2007. Finding very little difference in results, and lacking the time to repeat all the tests (these take several weeks) we report all regression results for the period ending in June 2007. However Figs. 1 and 4 are shown for the sample ending in September 2007.

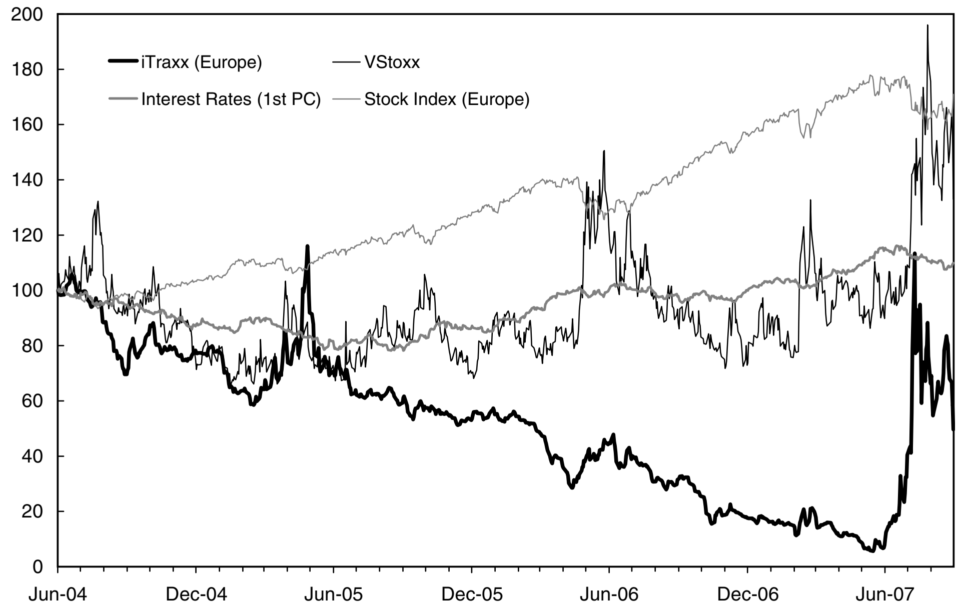

Fig. 1. The iTraxx Europe index and its determinants. All series are normalized to start at 100.

constraints and they are not influenced by special tax regulations (see Hull et al., 2004). To capture both the level and spread of the yield curve, we apply a principal component analysis, which is rolled over on a daily basis including the last 100 observations.

As in any highly collinear system, the first principal component is an almost equally weighted portfolio of rates of all maturities. Thus, a positive change in the first principal component is associated with a parallel upward shift in the yield curve. In our sample, the second principal component has a negative weight at the shortest maturity and weights increase almost linearly becoming positive at about eight years. Since the yield curve is upward sloping for the whole sample, an increase in the second component leads to a steeper yield curve and should therefore be accompanied by decreasing CDS spreads.

The advantage of using principal components instead of a risk-free interest rate for the level and the difference between a long rate and a short rate for the slope, as often done in previous studies, is twofold: it prevents using the difference between two arbitrary points of the yield curve and it eliminates the problem of collinearity that may arise when using the slope as an interest rate difference and the level as single interest rate. However, we also examine the effect of standard measures for level and slope. The 5-year swap rate serves as a proxy for the overall interest rate level and we choose the difference between the 10-year and 2-year rate as our slope proxy (see also Collin-Dufresne et al., 2001).

Our proxy for the equity value for the various iTraxx indices is an equally weighted portfolio of stocks consisting of the same constituents as the CDS indices. Hence the stocks selected vary accordingly to the changes in membership of iTraxx series. Since the iTraxx indices are equally weighted indices we create stock portfolios that are designed in the same way. Stock prices are downloaded from Bloomberg and Datastream. Whenever a firm in the sample does not have a traded stock or prices are not available on Bloomberg and Datastream, the firm is omitted from the stock portfolio, which increases the weight of the other companies in the index equally. This is only the case for a few firms in the sample and there are never more than four companies missing for any sub-index.

Lastly, as mentioned above, firm's asset volatility is unobservable and will be proxied by some measure of equity volatility. We consider two alternative measures: a statistical volatility based on historical stock return data and implied volatility based on the current values of stock options. Historical volatility is directly computed from the daily returns on the equally weighted stock portfolio and we choose the *VStoxx* index as a proxy implied volatility.[8] Since many of the firms lack (liquidly) traded options we cannot use single-firm option prices to construct a proxy for equity volatility. Index option implied volatilities are based on index option prices and therefore they reflect the current opinions of traders about the future movements in the index. Benkert (2004) found that implied volatility has a closer association with CDS spreads than does historical volatility. This is to be expected since, like CDS spreads, implied volatility is based on trader's expectations of the future whilst historical volatility is based only on past equity returns.

[8] *VStoxx* is an implied volatility index based on options on the DJ Eurostoxx 50. It can be downloaded from www.stoxx.com. This type of proxy is also used in Collin-Dufresne et al. (2001) (they call *VIX* the '*best available substitute*' for their data set) even though their research is related to single-firm bond-spreads. But we are dealing with an index spread so *VStoxx* should be a very good substitute.

Table 1
Linear regression results

Const.	CDS_{t-1}	ΔV	R	PC_1	PC_2	R^2	Adjusted R^2	AIC	SC
Europe									
−0.0181	0.3611	0.1369	−19.9841	−0.6899	0.3246	0.2745	0.2697	1.7466	1.7833
(−0.8472)	(11.585)	(3.2724)	(−3.8143)	(−3.6965)	(0.4163)				
High volatility									
−0.0361	0.3683	0.3269	−33.5531	−1.0892	0.2731	0.2653	0.2604	3.2245	3.2611
(−0.8129)	(11.7402)	(4.1446)	(−3.6607)	(−2.7821)	(0.1675)				
Non-financials									
−0.0320	0.2040	0.0938	−8.3655	−0.8821	0.6638	0.0919	0.0858	2.2461	2.2828
(−1.1668)	(5.8479)	(1.7863)	(−1.2458)	(−3.6862)	(0.6627)				
Financials senior									
−0.0229	0.1854	0.0145	−3.3609	−0.0378	−0.1022	0.0497	0.0434	0.4451	0.4818
(−2.058)	(5.2078)	(0.709)	(−1.5859)	(−0.3874)	(−0.2523)				
Financials subordinate									
−0.0245	0.3886	0.0511	−7.7089	−0.1812	−0.1157	0.1824	0.1769	1.5328	1.5695
(−1.2794)	(11.7669)	(1.4523)	(−2.1122)	(−1.0788)	(−0.1659)				

Results of regressing daily changes in European Itraxx CDS indices on theoretical determinants of CDS spreads. Regression coefficients and corresponding t-statistics (in parentheses) are reported.

Fig. 1 shows iTraxx Europe and VStoxx movements (left hand scale) and the evolution of our constructed stock market index and interest rates (right hand scale) over the whole sample period. From June 2004 to June 2006 the iTraxx index displays a stable downward trend interspersed with brief periods of volatility, notably in May 2005. But during July and August 2007 credit spreads soared as many European banks were forced to raise capital requirements to cover low grade credits, following the sub-prime mortgage crisis in the US.

4. Linear regression analysis

In this section, we estimate the following linear regression model for each CDS index h in our sample:

$$\Delta \mathrm{CDS}_{h,t} = \beta_{h,0} + \beta_{h,1}\Delta CDS_{h,t-1} + \beta_{h,2}\Delta V_t + \beta_{h,3}R_{h,t} + \beta_{h,4}PC_{1,t} + \beta_{h,5}PC_{2,t} + \varepsilon_{h,t}, \tag{1}$$

where $\Delta \mathrm{CDS}_{h,t-1}$ is the lagged CDS index change, ΔV_t is the change in the *VStoxx* volatility index, $R_{h,t}$ denotes the return of the hth stock index and $PC_{j,t}$ denotes the jth interest rate principal component.[9] The results are given in Table 1.

In the Europe Main and the High Volatility index the signs of all coefficients are as predicted by structural default models and are statistically significant except for the slope of the yield curve. According to theory, the second principal component should have a negative association with credit spreads but there is no significant evidence to support this assertion. The first principal component is significant (except in the financial indices) indicating that interest rate changes may indeed influence CDS spreads. We reach the same conclusion when we use the 5-year swap rate and the difference between 10 and 2 year swap rates as interest rate level and slope proxy, respectively.[10]

Table 2
Principal component analysis

	Eigenvector 1	Eigenvector 2
Cumulative probability	0.643	0.819
Europe	−0.481	0.399
High volatility	−0.490	0.414
Non-financials	−0.442	0.063
Financials senior	−0.358	−0.738
Financials subordinate	−0.453	−0.348

Below the cumulative probability are the eigenvectors belonging to the two largest eigenvalues of the correlation matrix of the residuals of regression (1).

Overall the results for the two most liquidly traded iTraxx indices (Europe Main and High Volatility) are the strongest, indicating that changes in structural variables are more quickly incorporated into the main indices. Implied volatility changes and stock returns both influence CDS spreads significantly in the Europe and High Volatility index. The identification of the separate influence on CDS spread changes of *VStoxx* on the one hand and stock returns on the other is a difficult task, since these variables display a high degree of collinearity. Their correlations in the sample exceed −70% for each index. However, the overall fit of the model deteriorates when either variable

[9] Since the input to principal component analysis must be stationary we use the first difference of swap rates. As a result the PC themselves are stationary and can be directly used in our regression without using first differences.

[10] The results for these interest rate proxies resemble the results displayed in Table 1. In particular significance levels and R^2 are very similar and the slope is insignificant in any index. We omit the results here.

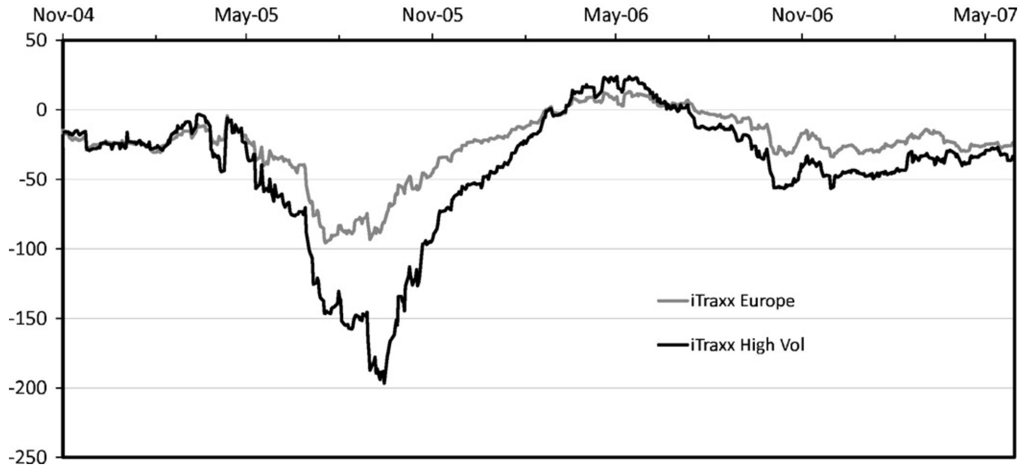

Fig. 2. Evolution of regression coefficients. The evolution of the value of the regression coefficient estimates on the stock portfolio returns with the changes in the Europe iTraxx index (grey line) and the High Volatility index (black line) as dependent variables. The regression (1) is rolled over on the previous 100 observations.

is excluded, and so we continue the analysis with both volatility and returns as CDS determinants.

Finally, we remark that any measure of historical volatility, such as that based on an equally or exponentially weighted moving average, has no significant association with CDS spreads in the model (1). For this reason we do not present results for any historical volatility measures in the remainder and conclude that only implied volatility has a close relationship with CDS spread changes.

Perhaps the most remarkable result is the highly significant influence of lagged changes of the iTraxx indices. For all indices the lagged dependent variable is by far the most significant factor. The first-order autocorrelation of the main series throughout the whole sample period amounts to 36.4% with a significance level of 0.000. Even higher order autocorrelation is significant at this level and equal results are obtained for the other indices. Weekly and monthly changes in iTraxx indices on the other hand exhibit weak negative autocorrelation. Our findings are similar to those of Byström (2005) who was the first to report the extremely high autocorrelation in daily changes in the iTraxx market. A persistent autocorrelation raises the question of inefficiencies in the iTraxx market. Recent research (Byström, 2006) however shows that it is not possible to exploit the autocorrelation with simple trading strategies when taking transaction costs into account.[11] Byström (2005) also reports that stock prices lead CDS prices and this finding could arise from the presence of autocorrelation in CDS indices. If there is both autocorrelation in CDS changes and a correlation between the stock index returns and CDS spread changes, the fact that lagged changes in stock returns are significant could be the result of collinearity, so it does not necessarily indicate a significant lead-lag relationship.

In some respects our results are similar to previous empirical studies on individual credit spreads. A principal component analysis on the residuals of the indices indicates that most of the variation that is not explained by regression (1) is due to a common factor. Indeed 64.30% of the variation is explained by the first principal component. The first two eigenvectors are given in Table 2. The first factor is a nearly equally weighted portfolio, indicating a systematic factor influencing residuals. Collin-Dufresne et al. (2001) find the same effect for single-name bond spreads and no relationship between the first principal component and economic variables. The second principal component in Table 2 indicates that there is a missing systematic factor that only affects CDS spreads on financial firms. We have estimated model (1) with further economic variables to account, for instance, for potential non-linearities in the influence of CDS determinants on credit spreads. Whilst we find some evidence of non-linearity in the relationship with interest rates, especially in the financial sector indices, even with the inclusion of these variables the first two eigenvectors remain almost unchanged. We conclude that any variable that may cause the systematic effects in the residuals are not related to structural models of credit spreads.

To test the stability of regression parameters, we apply a Chow breakpoint test (Chow, 1960) and calculate p-values for all dates in the sample except for the very first and very last 100 observations. The results show an extreme instability of regression coefficients for all indices. For the main index, in over 31% of sample observations, a Chow test rejects the null hypotheses of no break at a significance level of 1%. The results for the sub-indices are comparable apart from the financial senior index where the evidence of structural breaks is weaker. We further examine parameter stability by rolling the regression Eq. (1) over on a daily basis using the last 100 observations. The results for the Europe and high volatility index are shown in Fig. 2, which displays the evolution of the value of stock portfolio

[11] An example of a simple trading strategy is holding a long position after an increase in iTraxx spreads and a short position after a negative change.

coefficients. There is an increase in the influence of the stock indices towards summer 2005 of the sample. We conclude that CDS indices may have regime specific behaviour.

5. Markov switching models

Markov switching regression models allow the influence of explanatory variables to be state-dependent. Within model (1) this approach allows the regression parameters $\beta_{h,j}$ to change over time according to a particular transition probability and $\beta_{h,j}$ can take different values depending on the market regime or 'state' at time t, which is denoted by S_t. The transition from one state to another is described by an unobservable Markov chain, i.e.

$$\Delta \mathrm{CDS}_{h,t} = \beta_{S,h,0} + \beta_{S,h,1}\Delta CDS_{h,t-1} + \beta_{S,h,2}PC_{1,t} + \beta_{S,h,3}PC_{2,t} + \beta_{S,h,4}R_{h,t} + \beta_{S,h,5}\Delta V_t + \varepsilon_{S,h,t}. \quad (2)$$

Markov switching regressions go back to Goldfeld and Quandt (1973) and Cosslett and Lee (1985). The formulation used here is due to Hamilton (1989, 1994) who developed a statistical representation of unobservable states influencing the behaviour of a time series where the transition between the various states is modelled as a discrete-time, discrete-space Markov chain. Hamilton (1989) applied this framework to model the dependence of the real output growth on the business cycle. This triggered much research using Markov switching models for describing economic time series that exhibit breaks in their behaviour. Among the variables examined are stock returns, interest rates and exchange rates (see Turner et al., 1989; Perez-Quiros and Timmermann, 2000; Taylor, 2004; Bansal et al., 2004; Alexander and Dimitriu, 2005; Cheung and Erlandsson, 2005; Francis and Owyang, 2005; Clarida et al., 2006 and many others).

A Markov switching model allows the economy to be in one of n different regimes. The probability of a transition from state i at time t to state j at time $t+1$ is only influenced by the state at time t and not by any previous state. We further assume time independent transition probabilities, thus:

$$\mathrm{Prob}\{S_t = j | S_{t-1} = i, S_{t-2} = h, \ldots\} = \mathrm{Prob}\{S_t = j | S_{t-1} = i\} = p_{ij}$$

and these transition probabilities are summarised in the matrix $\mathbf{P} = (p_{ij})$. The Markov chain is represented by the random vector ξ_t, whose ith element equals one if $S_t = i$ and zero otherwise. Thus, in a two-state Markov chain $\xi_t = (0,1)\prime$ if $S_t = 2$. However, the Markov chain is assumed to be unobservable, thus we can never be sure about the regime at time t, we can only assign probabilities of being in one regime or another. The conditional expectation of ξ_{t+1} given t is denoted by $\xi_{t+1|t}$ and is calculated by premultiplying ξ_t by $\mathbf{P}$:

$$E(\xi_{t+1}|\xi_t) := \xi_{t+1|t} = \mathbf{P}\xi_t. \quad (3)$$

Under the assumption of Gaussian $\varepsilon_{i,t}$ for both states i, the conditional densities are represented by the vector $\boldsymbol{\eta}$ whose elements are given by

$$\boldsymbol{\eta}_{i,t} = f(y_t | S_t = i, \mathbf{x}_t, \boldsymbol{\psi}_{t-1}; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left\{ -\frac{(y_t - \mathbf{x}_t'\boldsymbol{\beta}_i)^2}{2\sigma_i^2} \right\},$$

where $\boldsymbol{\beta}_i = (\beta_{S_t=i,0}, \ldots, \beta_{S_t=i,5})'$, $\boldsymbol{\theta} = (\mathbf{P}, \boldsymbol{\beta}_i, \sigma_i)$ and $\boldsymbol{\psi}_{t-1} = (y_{t-1}, y_{t-2}, \ldots, \mathbf{x}_{t-1}, \mathbf{x}_{t-2}, \ldots)$ denotes the information up to time $t-1$. The vector $\boldsymbol{\eta}$ can be used in conjunction with the transition probabilities in (3) to derive the joint density of y_t, S_t and S_{t-1} conditional on $\boldsymbol{\psi}_{t-1}$ and $\mathbf{x}_t$:

$$f(y_t, S_t, S_{t-1} | \mathbf{x}_t, \boldsymbol{\psi}_{t-1}; \boldsymbol{\theta}) = f(y_t | S_t, S_{t-1}, \mathbf{x}_t, \boldsymbol{\psi}_{t-1}; \boldsymbol{\theta}) \cdot \mathrm{Prob}\{S_t, S_{t-1} | \psi_{t-1}\}.$$

Summing over all possible values for S_t and S_{t-1} leads to

$$f(y_t | \mathbf{x}_t, \boldsymbol{\psi}_{t-1}; \boldsymbol{\theta}) = \mathbf{1}'(\hat{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t),$$

where $\odot$ denotes element by element multiplication. The conditional state probabilities are obtained by recursively solving

$$\hat{\xi}_{t|t} = \frac{\hat{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t}{\mathbf{1}'(\hat{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t)}, \quad (4)$$

$$\hat{\xi}_{t+1|t} = \mathbf{P}\hat{\xi}_{t|t}. \quad (5)$$

The vector $\hat{\xi}_{t|t}$ is often referred to as the 'filtered' probability and is the best estimate for the Markov chain at time t given all information up to time t. The iteration in (4) and (5) leads to the conditional log likelihood of the observed data:

$$\log \mathfrak{L}(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log(\mathbf{1}'(\hat{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t)).$$

The set of optimal parameters $\hat{\boldsymbol{\theta}}$ can be obtained by maximising the log likelihood function under the restriction that probabilities sum to one ($\mathbf{P}'\mathbf{1} = \mathbf{1}$) and standard deviations are greater than zero ($\sigma_i \geqslant 0$). Given the parameter estimates we can also calculate smoothed probabilities of being in a particular state. Smoothed probabilities $\hat{\xi}_{t|\tau}$ use all the information in the data up to an observation τ ($\tau > t$, and usually $\tau = T$) as opposed to filtered probabilities which only use information up to time t to determine state probabilities. Kim's smoothing algorithm (see Kim, 1994) can be applied to recursively solve for $\hat{\xi}_{t|\tau}$ starting with $\hat{\xi}_{\tau|\tau}$.

6. Model estimation, inference and interpretation

Using the methodology described in the last section we estimate model (2) using a two-state Markov switching regression where the error process also has a state-dependent volatility. This volatility and all coefficients $\beta_{S,h,j}$ with $S \in \{1,2\}, h = 1, \ldots, 5$ and $j = 0, \ldots, 5$ are estimated by maximum likelihood and the results are displayed in Table 3.

Table 3
Markov switching regression results

	Const.	CDS_{t-1}	ΔV	R	PC_1	PC_2	Standard deviation	p_{ii}	AIC	SC
Europe										
Regime 1	−0.0351	0.3545	0.2955	−42.4796	−2.3373	0.9880	17.7527	0.9355	1.1702	1.2685
	(−0.2894)	(5.5637)	(1.197)	(−1.2261)	(−1.9468)	(0.2146)				
Regime 2	−0.0159	0.3535	0.0656	−18.6833	−0.3605	0.1352	5.1702	0.9869		
	(−1.13)	(11.2936)	(2.7429)	(−5.8841)	(−3.0354)	(0.2598)				
High volatility										
Regime 1	0.0023	0.3120	1.6847	−91.2195	−4.5398	4.8482	44.7125	0.9321	2.5580	2.6564
	(0.006)	(3.352)	(2.4077)	(−0.9719)	(−1.0362)	(0.2796)				
Regime 2	−0.0449	0.3854	0.1805	−30.8963	−0.7239	−0.6197	11.3997	0.9932		
	(−1.5416)	(12.8926)	(3.608)	(−5.4258)	(−2.8171)	(−0.5712)				
Non-financials										
Regime 1	−0.0643	0.2039	0.6626	−6.6586	−2.8274	1.2113	22.7810	0.8220	1.5490	1.6473
	(−0.4276)	(3.0634)	(2.3486)	(−0.1454)	(−2.4229)	(0.2295)				
Regime 2	−0.0240	0.1996	−0.0742	−12.7593	−0.4119	0.0297	5.6142	0.9614		
	(−1.4922)	(5.1111)	(−2.2618)	(−3.1174)	(−2.7564)	(0.0468)				
Financials senior										
Regime 1	−0.0104	0.2025	0.0329	−6.7192	−0.0678	−0.2257	7.7389	0.8627	−0.1369	−0.0385
	(−0.2831)	(4.151)	(0.4938)	(−0.8293)	(−0.2375)	(−0.1804)				
Regime 2	−0.0348	0.0764	−0.0080	−1.8697	0.0196	−0.1031	1.9091	0.9333		
	(−5.6305)	(1.9095)	(−0.6677)	(−1.6305)	(0.3694)	(−0.4454)				
Financials subordinate										
Regime 1	−0.0211	0.4399	0.1244	−28.7928	−0.6479	−0.9760	14.8821	0.8304	0.8649	0.9633
	(−0.2472)	(5.7015)	(0.8255)	(−1.6139)	(−0.8459)	(−0.3083)				
Regime 2	−0.0419	0.1817	0.0037	−2.5826	0.0417	0.3302	3.6233	0.9489		
	(−3.9008)	(5.4092)	(0.1817)	(−1.2507)	(0.4727)	(0.8465)				

Results of a Markov switching regression of changes in European iTraxx CDS indices on theoretical determinants of CDS spreads. Each regression coefficient and corresponding z-statistics (in parentheses) is reported. The regime dependent standard deviation is quoted in annualised basis points.

The coefficient estimates differ markedly between the two regimes. For the interpretation of the results we concentrate on the two most liquid indices, i.e. the Europe and high volatility indices. The first market regime is far more volatile than the second. For instance in the Europe index the average annual volatility of the error term is 17.75 bps in regime one (high volatility) compared with 5.17 bps during regime two (low volatility). We summarise the regime specific determinants of CDS spreads as follows:

- Changes in the stock market return and *VStoxx* volatility index have a significant effect in the second regime, where an increase in volatility and a decrease in the stock index lead to higher CDS spreads, as theory suggests. However, CDS spreads are not significantly affected by stock market returns during the first regime, where implied volatility has a stronger effect.
- The first interest rate principal component is highly significant only in the second regime. The direction of influence is as predicted by theory: a rise in interest rates leads to a decline in CDS spreads.
- The second interest rate principal component does not significantly influence CDS spreads in either regime.
- Lagged changes of the iTraxx Europe and the high volatility index are statistically significant in both regimes. In addition their coefficients are very much alike.
- The size of all regression coefficients is much higher during the volatile regime, when the association between CDS spreads and their structural determinants is enhanced.

Similar patterns are observed in Table 3 for the financials and non-financials sectors. The residual volatility in regime one is at least four times larger than the residual volatility in regime two; the stock market returns are more significant than implied volatility changes in the second regime whereas the impact of implied volatility changes is more pronounced during a volatile CDS regime; and the strength of autocorrelation is broadly similar in each regime.

The influence of interest rates on CDS spreads depends on the sector. Banks and other financial firms tend to have

Table 4
Test for equal determinants in both regimes

H_0 : no switching in all variables	LR statistic	p-value	Wald statistic	p-value
Europe	14.832	0.011	11.221	0.047
High volatility	19.738	0.001	33.298	0.000
Non-financials	26.859	0.000	28.789	0.000
Financials senior	7.188	0.207	8.787	0.118
Financials subordinate	27.922	0.000	28.767	0.000

The results of LR and Wald tests for equality of all coefficients in both regimes. In addition corresponding p-values are given.

Table 5
Test for equal VStoxx and stock return coefficients

	H_0 : no switching in stock returns				H_0 : no switching in *VStoxx*			
	LR	p-value	Wald	p-value	LR	p-value	Wald	p-value
Europe	6.376	0.012	6.376	0.012	8.405	0.004	6.894	0.009
High volatility	11.473	0.001	9.737	0.002	16.463	0.000	20.743	0.000
Non-financials	11.253	0.001	9.022	0.003	18.700	0.000	18.670	0.000
Financials senior	4.075	0.044	3.005	0.083	3.926	0.048	3.499	0.061
Financials subordinate	13.335	0.001	10.086	0.001	10.833	0.001	9.161	0.002

The results of LR and Wald tests for equality of ΔV and R. In addition corresponding p-values are given.

more short-term funding than non-financial firms so their debt repayments are more sensitive to an increase in short-term interest rates. On the one hand financial firms may benefit from higher interest rate payments by borrowers. Hence in the financial sector interest rates have an ambiguous relationship with CDS spreads. In fact our results for the two financials sub-indices show that interest rates have no significant effect on CDS spreads in either regime. The positive effects of an increased risk neutral drift and higher interest rate payments by borrowers appear to be cancelled out by the negative effect of higher debt repayments. However, in other sectors the general level of interest rates has a significant and negative effect on credit spreads in both regimes, especially in the tranquil regime.

Formal statistical tests of a Markov switching model against its linear alternative face the problem of unidentified parameters under the null hypothesis. For this reason standard tests do not converge to their usual distribution. For example when testing model (1) against model (2) the limiting distribution for a likelihood ratio test is not χ^2. Alternative tests have been suggested that produce valid inference (see Hansen, 1992, 1996; Carrasco et al., 2004; Rydén et al., 1998). In our case the large number of model parameters imposes a severe computational restriction on the application of these tests and we therefore focus on the Europe index in the first instance.

We follow Rydén et al. (1998) and use a Monte Carlo approach to test the null hypothesis of one regime against the alternative hypothesis of two regimes for the Europe index. That is, we obtain the empirical distribution of the likelihood ratio statistic via simulated data and compare this with the actual statistic from our data set. Since this procedure requires the estimation of model (2) for every iteration, it is very computationally intensive. We therefore set a limit of 200 simulations and used 40 randomised starting values for each simulation. The LR statistic from the actual data is 454.62 but the largest ratio obtained via simulations is 84.12. This provides very strong evidence in favour of two distinct regimes.

For all sub-indices we also test whether the influences of CDS determinants are stable over time whilst still allowing CDS volatility to follow a Markov switching process. That is, as in Engel and Hamilton (1990) we perform both likelihood ratio (LR) and Wald tests for the null hypothesis:

$$H_0: \ \beta_{S_t=1,j} = \beta_{S_t=2,j} \quad \text{for all } j, \sigma_1 \neq \sigma_2. \tag{6}$$

Note that this hypothesis is more conservative than the hypothesis that coefficients and residual volatility are identical. Both statistics are asymptotically $\chi^2(5)$ distributed and Table 4 presents the results. These indicate very strong evidence of switching in at least one variable in every index apart from the Financials Senior index.

Subsequently tests for switching in each individual variable indicates strong evidence of switching in the stock market determinants but little evidence of switching in either interest rate determinants or in the autocorrelation (i.e. the coefficient on the lagged dependent variable). The tests of switching in stock market variables are affected by the presence of multicollinearity between stock market returns and implied volatility. Therefore, we also tested for switching in Markov switching models with only one of the stock market variables. The results are presented in Table 5 and show that the null-hypothesis of no switching in the stock returns relationship can be rejected for all indices.[12] Evidence of switching in the relationship between stock volatility and credit spreads is even stronger.

Now we compare the unconditional density of the changes in the iTraxx Europe index with the unconditional density generated by (a) the linear model with no regime switching and (b) the Markov switching model. This allows to visualise the superiority of the switching model compared with the linear model. Let $f_{\mathrm{MS}}(y;\hat{\boldsymbol{\theta}})$ denote the unconditional density of the Markov switching model. We estimate $f_{\mathrm{MS}}(y;\hat{\boldsymbol{\theta}})$ by non-parametric kernel methods with 50,000 simulated observations of model (2). Similarly we obtain a kernel for changes in the iTraxx Europe under the assumption of a linear regression model (its density is denoted by $f_{\mathrm{LR}}(y;\hat{\boldsymbol{\theta}})$). Fig. 3 displays the density estimates for the Markov switching model, the linear regression model and the density implied by the observed data (denoted by $\hat{f}(y)$) of the iTraxx Europe index.

It is obvious that a Markov switching regression provides a much better representation of the observed data than a linear regression model. In particular the tails of the distribution are only well captured by the switching model. Whilst the switching model also improves the fit

[12] The financials senior index is the only one without strong evidence for switching.

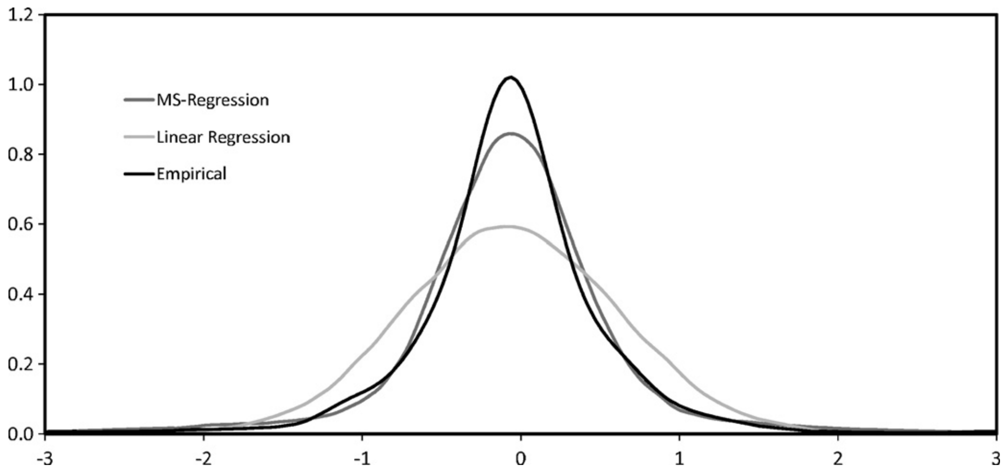

Fig. 3. Unconditional density estimates. The empirical distribution of changes in the iTraxx Europe Index and simulated distributions from the linear regression model and the Markov switching model.

Table 6
Markov switching regression results (tested down)

	Const.	CDS_{t-1}	ΔV	R	PC_1	PC_2	Standard deviation	p_{ii}	AIC	SC
Europe										
Regime 1	0.0095	0.3746		−84.8345			18.4268	0.9415	1.1705	1.2443
	(0.0823)	(6.3746)		(−3.9187)						
Regime 2	−0.0170	0.3547	0.0729	−18.0892	−0.3808		5.2014	0.9883		
	(−1.2126)	(11.5076)	(3.2346)	(−6.0616)	(−3.2458)					
High volatility										
Regime 1	0.1192	0.3306	2.4126				46.0929	0.9333	2.5518	2.6255
	(0.313)	(3.9842)	(6.1131)							
Regime 2	−0.0463	0.3820	0.1803	−30.6593	−0.7590		15.8114	0.9936		
	(−1.5913)	(13.025)	(3.6384)	(−5.4393)	(−2.9975)					
Non-financials										
Regime 1	−0.0705	0.2059	0.7073		−2.8090		22.7997	0.8219	1.5411	1.6211
	(−0.4858)	(3.1203)	(4.5648)		(−2.4427)					
Regime 2	−0.0238	0.1997	−0.0748	−12.8573	−0.4105		5.6162	0.9614		
	(−1.4918)	(5.1245)	(−2.2986)	(−3.1943)	(−2.7545)					
Financials senior										
Regime 1	−0.0092	0.2096		−9.8743			7.5573	0.8638	−0.1515	−0.1023
	(−0.2797)	(4.6779)		(−2.5449)						
Regime 2	−0.0399						1.8446	0.9279		
	(−6.8078)									
Financials subordinate										
Regime 1	−0.0177	0.4380		−38.7653			14.6135	0.8274	0.8561	0.9114
	(−0.2273)	(6.3893)		(−4.0785)						
Regime 2	−0.0439	0.1757					3.5309	0.9433		
	(−4.1755)	(5.4862)								

The results of a Markov switching regression of changes in European iTraxx CDS indices on theoretical determinants of CDS spreads. Each regression coefficient and corresponding z-statistics (in parentheses) is reported. The regime dependent standard deviation is quoted in annualised basis points.

around the mode of the distribution considerably, it cannot capture its peak completely. For this reason statistical tests reject the hypothesis that the MS switching density equals the unconditional density of the data over the whole sample period.[13] The extreme peak around the mode mainly results from a long period at the end of the sample where low volatility prevailed in the iTraxx index market. We remark that the test derived by Ait-Sahalia (1996) based on the first 60% of the data set shows that the Markov switching regression fits the mode extremely well and that the null hypothesis of equal densities cannot be rejected. We can conclude that the Markov switching model far outperforms its linear alternative.

Having demonstrated this highly significant regime switching behaviour we now reduce the parameters of the models in Table 3 by excluding all variables which do not

[13] We test the null-hypothesis of equal densities following the method suggested by Ait-Sahalia (1996) (for applications to Markov switching models see also Breunig et al., 2003).

have a significant influence on the iTraxx indices. The tested-down model for the main iTraxx Europe index is as follows:

Regime one:

$$\Delta CDS_t = \underset{(0.0823)}{0.0095} + \underset{(6.3746)}{0.3746}\,\Delta CDS_{t-1} - \underset{(-3.9187)}{84.8345}\,R_t$$

and

Regime two:

$$\Delta CDS_t = \underset{(-1.2126)}{-0.0170} + \underset{(11.5076)}{0.3547}\,\Delta CDS_{t-1} - \underset{(-6.0616)}{18.0892}\,R_t + \underset{(3.2346)}{0.0729}\,\Delta V_t - \underset{(-3.2458)}{0.3808}\,PC_{1,t}.$$

The tested-down models for the iTraxx sub-indices given in Table 6. The high volatility and non-financials sub-indices follow very similar patterns to the main Europe index: all theoretical determinants except for the slope of the yield curve are highly significant during the tranquil market regime. Since the association between equity value and credit spreads is strong in low-rated companies, stock returns are significant determinants of CDS spreads in both of these sub-indices, but only during ordinary market circumstances. Once volatility has entered the CDS market there is no doubt that option implied volatilities become the most important determinant of credit spreads. This is because the price of a CDS become more sensitive to volatility when the firm value is close to the default-triggering barrier, so investors may become more concerned about future uncertainties once volatility has entered the CDS market.

However CDS spreads in the financial sectors behave differently. Firstly, for reasons explained above interest rate changes have no significant effect on credit spreads. Secondly it is the stock return that is most significant during the volatile regime, even though stock returns have no effect on CDS spreads during ordinary circumstances. Finally, autocorrelation in CDS spreads is only apparent during volatile periods for the financials senior index.

Yu (2005) empirically investigates the success of capital structure arbitrage between CDS and equity markets, assuming the markets have only one state. Capital structure arbitrage exploits the mispricings between credit, bond and equity markets. If a comparison of the market CDS spread with the theoretical spread from a structural model indicates a significant mispricing, an appropriate trade is made and the exposure of the position to the stock market is hedged. Yu (2005) finds that empirical hedge ratios can be completely ineffective during volatile periods. Our results can explain this finding because it is necessary to distinguish between market regimes when determining an appropriate hedge ratio.

7. What drives the regime transitions?

We already know that the volatility of the Markov switching model residuals is much greater in state one and so we have called this the volatile regime. It seems reasonable to suppose that CDS spreads will themselves be more volatile when the volatility of the residuals is high. Fig. 4 supports this by comparing the filtered probabilities of the Europe index being in state one with the squared changes of the index. Notice that a switch to the volatile regime is often but not always accompanied by a jump in the CDS volatility.

The first time we enter the volatile regime in our sample is on August 18th 2004 when the iTraxx Europe index fell by 3 bps in two days. Further downward jumps in credit spreads precipitated the volatile regime until the beginning of October 2004. A significant rise in volatility between March and May 2005 began when General Motors (GM) stocks slumped after a profit warning on March 16th

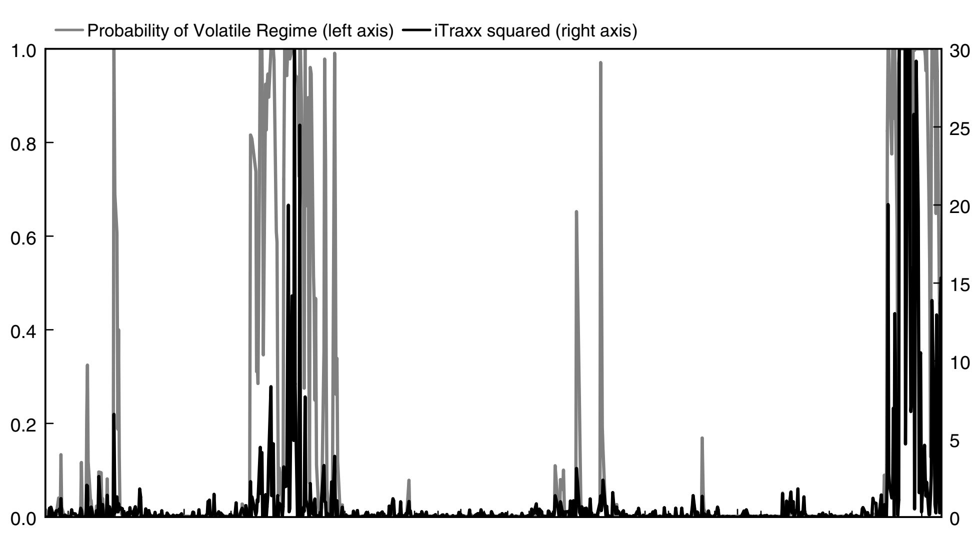

Fig. 4. Regime probabilities and CDS volatility. The filtered probability of being in the volatile regime (grey line and left hand scale) and the squared changes in the iTraxx Europe index (black line and right hand scale).

2005 and GM bonds were put on the watchlist by Standard & Poor's. At the beginning of May 2005, when the major rating agencies eventually announced the downgrade of GM bonds from investment to junk status, the iTraxx Europe index rose by 11 bps in only 4 days. This volatile regime remained until July 13th 2005. Another volatile period can be observed during May and June 2006 when financial markets were going through a turbulent phase. The last time the volatile regime ruled was during the US sub-prime mortgage crisis in July and August 2007. At the beginning of September 2007 credit spreads returned to the tranquil regime, but only for a few days because further sharp increases in the iTraxx again precipitated the volatile regime at the end of the sample.

GM is not a member of the iTraxx Europe CDS series, nevertheless the speculation on its downgrade and the downgrade itself made investors aware of the risks involved in credit default swaps and eventually led to a highly volatile CDS market in Europe for several weeks. This indicates that CDS premiums may be influenced by the expected creditworthiness of major companies. Hence changes in their ratings, or even public discussions about credit rating deterioration, can raise volatility in the CDS market. Also major events such terrorist assaults can increase CDS volatility in all markets. For instance, after September 11th there was very high volatility in the European CDS market.

The question of causality between CDS spread volatility and regime switches can be addressed by estimating a logit model for each index, of the form

$$p_t = \frac{1}{1 + \exp(-\alpha_0 - \alpha_1 x_{t-1})}, \tag{7}$$

where p_t denotes the filtered probability of being in the volatile regime at time t, α_0 and α_1 are regression coefficients and x_t is the squared change in the iTraxx index. Estimates for α_0 and α_1 (denoted by a_0 and a_1) are obtained by maximum likelihood. The results are shown in the first column of Table 7. The sign and significance of the coefficients for each index indicate that a large jump in the credit spread, up or down, may indeed be followed by a regime shift.

We also ask whether it is possible to find a structural variable that forces CDS spreads from one regime to another. Investors' fear of credit deterioration may be incorporated in option prices, since credit deterioration is often accompanied by large negative jumps in stock prices. Measures of stock market jump risk are often related to the shape of the implied volatility surface. For instance, Collin-Dufresne et al. (2001) measure investors' expectation of jump risk using the difference between 90%-moneyness implied volatility and at-the-money implied volatility of the closest-to-maturity options. However the implied volatility smile tends to become steeper when the option expiry approaches and thus an increase in this measure cannot be attributed to jump risk alone. The dependence of the smile on the time to maturity indicates that a changes in the slope of a constant maturity smile would be a better measure of jump risk (see for example Hafner and Wallmeier, 2001).

VStoxx indices exist for different constant maturities from one month to two years, and this allows us to consider the slope of the term structure of implied volatilities as a proxy for jump risk. A decrease in short-term volatility compared with long-term volatility indicates that downward jumps in equity prices are considered less likely over the short-term than over the medium and longer term. The *VStoxx* indices are highly correlated, so we can apply

Table 7
Logit model

Index	$\Delta \mathrm{CDS}^2_{t-1}$	j_{t-1}	$\Delta \mathrm{CDS}_{t-1}$	ΔV_{t-1}	R_{t-1}	$\mathrm{PC}_{1,t-1}$	$\mathrm{PC}_{2,t-1}$
Europe							
	0.9547	0.0674	0.2457	0.0961	−26.8418	−2.395	−10.4345
	(14.3757)	(0.2336)	(1.1386)	(0.5584)	(−1.2495)	(−1.9282)	(−2.0267)
	[0.2183]	[0.0001]	[0.0017]	[0.0004]	[0.0021]	[0.005]	[0.0055]
High volatility							
	0.2814	−0.5223	−0.0808	−0.3655	14.6312	−2.9898	−5.1387
	(14.3996)	(−1.7536)	(−0.7201)	(−2.0363)	(0.7113)	(−2.3518)	(−0.9686)
	[0.2189]	[0.0042]	[0.0007]	[0.0056]	[0.0007]	[0.0074]	[0.0013]
Non-financials							
	0.5623	−0.3394	−0.2616	−0.2048	7.4484	−1.3485	−7.57
	(9.4414)	(−1.2168)	(−1.3626)	(−1.2117)	(0.3476)	(−1.1223)	(−1.5268)
	[0.1087]	[0.002]	[0.0025]	[0.002]	[0.0002]	[0.0017]	[0.0032]
Financials senior							
	3.588	0.2076	−0.2813	0.0867	−38.7885	−1.00	−3.0284
	(7.2639)	(0.6018)	(−0.4907)	(0.4168)	(−1.8261)	(−0.6693)	(−0.4908)
	[0.0675]	[0.0005]	[0.0003]	[0.0002]	[0.0046]	[0.0006]	[0.0003]
Financials subordinate							
	1.2534	−0.1225	0.0585	−0.1688	4.295	−1.9975	−1.9975
	(11.1067)	(−0.3433)	(0.1906)	(−0.7923)	(0.1968)	(−1.3139)	(−1.3139)
	[0.1434]	[0.0002]	[0.0000]	[0.0009]	[0.0001]	[0.0023]	[0.0023]

The a_1 coefficients from the logit regressions. In addition t-statistics (in parentheses) and R^2 (in square brackets) are given.

principal components to this term structure just as we have done for interest rates. The second principal component can be interpreted as a measure of change in the slope of the term structure. The second eigenvector is decreasing with maturity, a positive second principal component therefore captures an increase in short-term volatility compared with long-term volatility. This implies an increase in the risk that stock prices will jump downward in the short-term but a decrease in the risk of such a jump over a longer horizon.

We have estimated (7) using several jump risk proxies for the explanatory variable x, but with little success. The second column of Table 7 presents the results when the jump proxy is the slope of the *VStoxx* term structure. We cannot conclude that this, or any other of our jump risk proxies, is significantly related to a switch in regime.

Subsequently, we used the same logit model to investigate whether lags of the endogenous variables of model (2) can explain why credit spreads move in and out of the volatile regime. Table 7 displays the results for all these variables. The first principal component of the yield curve ($PC_{1,t-1}$) has a negative sign in all of the indices. This indicates that raising interest rates may decrease the probability that credit spreads enter the volatile regime. However this is the only structural variable that seems to have any explanatory power for driving the switches between regimes.

8. Summary and conclusions

This study investigates the influence of theoretical determinants on the daily changes in the iTraxx Europe indices during a three year period between June 2004 and June 2007. The following results are consistent with previous empirical studies on credit spreads:

- Theoretical determinants of structural credit risk models, i.e. interest rates, stock returns and implied volatility each has a significant effect on CDS spreads (Benkert, 2004; Ericsson et al., 2004; Byström, 2005). In fact the only theoretical variable that has no significant influence for our sample is the slope of the yield curve.
- However only about 20–30% of the variation in credit spreads can be explained and most of the unexplained variation is due to a systematic factor (see Collin-Dufresne et al. (2001) for bond spreads).

The new results in this paper are founded on the strong evidence that the influence of theoretical determinants of credit spreads has a regime dependent, sector specific behaviour.

The association between credit spreads and their determinants depends very much on the market circumstances prevailing at the time, and on the volatility of the CDS market in particular. In volatile regimes the iTraxx index changes are more sensitive to changes in implied volatility, whereas in tranquil regimes it is the stock market returns that have the main influence on credit spreads. Policy makers should be interested to know that credit spreads are only sensitive to changes in the level of the yield curve during tranquil periods, and then only in non-financial sectors.

CDS on financial firms behave quite differently from CDS on non-financial firms and low rated companies. First, financial firms may benefit from small interest rate increases, but not if they are so large that debt repayment problems ensue. We find that CDS spreads on financial firms are immune to interest rate changes. However interest rates have a negative association with credit spreads in all other sectors.

We have investigated whether economic variables force switches in the CDS index regime, focusing on a proxy for jump risk, but the relationships were weak. We found some evidence that raising interest rates decreases the probability of credit spreads entering the volatile regime and that jumps in credit spreads, particularly upward jumps, can raise the probability of entering the volatile regime. No other variables provided a satisfactory explanation of the transition from one regime to another.

Our models have more explanatory power in the volatile regime, so the association between CDS spreads, interest rates, stock returns and option implied volatility is much stronger when the iTraxx indices are volatile. Previous research by Cossin et al. (2002) and others has shown that structural variables explain more variation in credit spreads when they have lower credit quality. Therefore our results suggest that during periods of 'crisis' CDS indices adopt the behaviour of higher-risk CDSs and become more sensitive to structural variables, even though the creditworthiness need not have changed.

Equity hedge ratios are highly sensitive to the regime, being three or four times larger during the volatile regime. The Markov switching model provides an estimate of the regime probability and hence a superior determination of the appropriate hedge ratio. This should be of particular interest to CDS traders or investors that wish to hedge the equity risk of their CDS positions. It also explains why Yu (2005) finds that equity hedges can be completely ineffective during periods of crisis. Only regime dependent hedge ratios can reduce stock market exposure as desired.

The iTraxx CDS market displays volatility clustering features that are similar to those in many other financial markets. Once volatility has entered the market it is quite persistent. For instance, in the main iTraxx Europe series the probability of remaining in the volatile regime is 94%. The persistence is even higher for the tranquil regime, with a probability of 99% of remaining in the regime once there, and the tranquil regime was the predominant regime for all indices during our sample, with over 80% of all observations belonging to it.[14] Furthermore, there is also a pro-

[14] The persistence in volatility for CDS spread is similar to that observed in a typical stock market. For this comparison, we estimate a two-state $AR(1)$-Markov switching model with state dependent volatility for the Eurostoxx 50 equity index. We find that over the same three year data period, the persistence of the tranquil stock market regime is very high with 99.4%. The probability of remaining in the volatile state is 95.6% and is therefore similar to that in the CDS market.

nounced autocorrelation in daily iTraxx index changes. Weekly and monthly changes display a weak negative autocorrelation, indicating a slow mean reversion of the spread in the long run. Our results offer some of the first insights in the literature to the price dynamics of iTraxx indices. The development of a suitable mean-reverting conditionally heteroscedastic process for the iTraxx price dynamics is an interesting topic for future research.

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