European Asset Swap Spreads and the Credit Crisis

Wolfgang Aussenegg(a), Lukas Götz(b), and Ranko Jelic(c)*

(a) Department of Finance and Corporate Control, Vienna University of Technology
Address: Theresianumgasse 27, A-1040 Vienna, Austria
E-mail: waussen@pop.tuwien.ac.at, Phone: +43 1 58801 33082

(b) UNIQA Finanz-Service GmbH
Address: Untere Donaustraße 21, A-1029 Vienna, Austria
E-mail: lukas.goetz@uniqa.at, Phone: +43 1 211 75 2012

(c) Business School - Department of Accounting and Finance, University of Birmingham
Address: Birmingham, B15 2TT, United Kingdom
E-mail: r.jelic@bham.ac.uk, Phone: +44 (0) 121 414 5990

*Corresponding author

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Abstract

We examine time-varying behavior and determinants of asset swap (ASW) spreads for 23 iBoxx European corporate bond indexes from January 2006 to January 2009. The results of a Markov switching model suggest that ASW spreads exhibit regime dependent behavior. The evidence is particularly strong for Financial and Corporates Subordinated indexes. Stock market volatility determines ASW spread changes in turbulent periods whereas stock returns tend to affect spread changes in periods of lower volatility. Whilst market liquidity affects spreads only in turbulent regimes the level of interest rates is an important determinant of spread changes in both regimes. Finally, we identify stock returns, lagged ASW spread levels, and lagged volatility of ASW spreads as major drivers of the regime shifts.

JEL classification: C13, C32, G12

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1. Introduction

An asset swap (ASW) is a synthetic position that combines a fixed rate bond with a fixed-to-floating interest rate swap.[1] The bondholder effectively transforms the payoff, where she pays the fixed rate and receives the floating rate consisting of LIBOR (or EURIBOR) plus the ASW spread. In case of a default the owner of the bond receives the recovery value and still has to honor the interest rate swap. The ASW spreads is a compensation for the default risk and corresponds to the difference between the floating part of an asset swap and the LIBOR (or EURIBOR) rate. Corporate bonds are always quoted with their ASW spreads and their pricing is based on the spreads. ASWs are very liquid and could be traded separately, even easier than underlying defaultable bonds (Schonbucher, 2003). ASW spreads are, therefore, a bond specific measure of credit risk implied in bond prices and yields. ASWs are closely associated with credit derivatives such as credit default swaps (CDS).[2] For example, asset-swapped fixed-rate bonds financed in the repo market are comparable to CDS contracts (Francis et al., 2003). ASW usually trade in a close range (see Norden and Weber, 2009, and Zhu, 2004) and tend to be cointegrated with CDS (De Wit, 2006).[3]

Previous studies examine determinants of credit spreads inferred from CDS indexes (Byström, 2005; Alexander and Kaeck, 2008; Naifar, 2010; Bembouzid and Mallick, 2013), single name CDS spreads (Yu, 2005; Benkert, 2004; Erricson et al., 2004; Cossin et al., 2002; Hull et al., 2004**;** Fabozzi et al. 2007; Tang and Yan, 2010), individual corporate bonds (Collin-Dufresne et al., 2001; Tsuji, 2005), and bond portfolios/indexes (Pedrosa and Roll, 1998; Brown, 2000).

There was, however, no previous study on determinants of credit spreads inferred from ASW indexes. Our objective is twofold. First, we examine determinants of ASW spreads for the first time in the literature. Second, we examine the time-varying nature of the association of ASW spreads and their economic determinants. The examination of ASW spreads across different industries and in different regimes is important for the following reasons. First, the cross-sectional effects of regimes on asset returns, especially in large samples, were identified as an important area for future research. For example, Ang and Timmermann (2011) find that most work in asset pricing incorporating regime switching has considered either a single or a small set of risky assets. Cross-sectional effects of regimes on asset returns have been, therefore, far less studied.[4] Consideration of credit spreads in different market regimes is also important for practitioners involved in trading strategies involving mispricing between credit, bond and equity markets. For example, some of the empirical hedge ratios used in the above strategies may become less effective when market exhibits regime switching behaviour (see Yu, 2005; Alexander and Kaeck, 2008). Furthermore, the hedge ratios may be affected by different factors (e.g. industry related or global) in different market regimes (Aretz and Pope, 2012).[5]

Second, previous studies rarely examine industry portfolios although individual assets and industry portfolios may differ in terms of their sensitivity and exposure to regime changes (Ang and Timmermann, 2011; p. 19). Furthermore, studying credit spread indexes (rather than credit spreads for individual bonds) is particularly useful in order to shed light on the systematic components of credit valuation that resist elimination by diversification (Pedrosa and Roll, 1998). Availability of numerous ASW indexes allows us to examine the systematic components of credit risk in industry and portfolios constructed for different credit ratings, seniority and regulatory considerations.

Finally, the bond market is characterized by a relatively high trade frequency and small average trade size compared to the CDS market (IOSCO, 2012). A combination of netting, centralized clearing, and reduced spreads contributed to a 48% fall in notional amounts outstanding of CDS worldwide, from $58 trillion at the end of 2007 to $30.3 trillion at the end of June 2010 (IFSL, 2012; p. 5). At the same time, the issuance of investment grade bonds in European markets has increased almost three-fold, reaching the €140 billion mark at the beginning of 2009 (IFSL 2009).[6] Due to the limited trading in CDS names, CDS indexes are not available for all industries (e.g. Health care, Automobiles and parts, Utilities, etc.). On the other hand, given that asset swaps are synthetic positions that combine fixed-bond coupon payments and fixed-for-floating rate swap transactions, we can calculate ASW indexes for any industry (even for industries where no ASW trading takes place) with a liquid market for (individual) bonds. Furthermore, Mayordomo et al. (2011) raise doubts about the representativeness of prices quoted in the CDS market during periods of financial crisis and diminishing liquidity. When liquidity drops sharply, CDS movements are more likely to be unrelated to default expectations. Consistent with the above, Mayordomo et al. (2011) show that during the recent crisis ASW spreads led CDS spreads and, thus, proved to be a more efficient indicator of credit risk.

Most related to our work is the study of Alexander and Kaeck (2008) who examine determinants of iTraxx Europe CDS indexes. Their analysis however was limited to a pre-crisis period (June 2004-June 2007). In addition, due to the lack of availability of CDS indices for different sectors, their focus was on available iTraxx Europe CDS indexes: main, non-financials, high volatility, financials senior and financials subordinated. We, therefore, contribute to the literature by examining determinants of ASW spreads for 10 industries (Automobiles, Chemicals, Food and Beverages, Health Care, Oil and Gas, Personal and Household Goods, Retail, Telecommunications, Utility, and Banks) and 13 composite iBoxx indexes stratified by industry grouping (Corporates, Financials, Non-Financials), credit rating (from AAA to BBB) and seniority (Senior and Subordinated), in different market regimes. We also extend the Alexander and Kaeck (2008) model for determinants of credit spreads by considering market liquidity.

Our main findings are: (i) ASW spreads behave differently during periods of financial turmoil, with a residual volatility which is up to eight times higher compared to calm periods; (ii) structural determinants explain ASW spreads better for financial sector companies than for the remaining industry sectors; (iii) we find little evidence of regime switching in non - cyclical industry sectors (e.g. Utility, Chemicals, Telecoms); (iv) the financial sector shows a high degree of autocorrelation in ASW spreads, which is mostly negative in calm but highly positive in turbulent market periods; (v) stock market volatility determines ASW spreads mainly in turbulent periods whereas stock returns are more important in periods of lower volatility; (vi) interest rates are an important determinant in both market regimes; (vii) the liquidity premium, defined as the difference between the swap and the government bond yield curve tends to be relevant only in turbulent regimes; (viii) raising stock market returns and interest rates tend to reduce the probability of entering the volatile regime; (ix) our Markov switching model exhibits better accuracy than the equivalent OLS model for determinants of ASW spreads.

The remainder of this paper is organized as follows: Section two motivates our hypotheses. Section three describes data and methodology. In section four we present results of our Markov switching model. In section five, we discuss the economic identification of the regimes and examine the main drivers of the regime switching. This is followed by various robustness checks performed in section six. Finally, section seven sums up and concludes.

2. Literature and hypotheses

The pricing of credit risk has evolved in two main approaches. First, reduced form models treat default as an unpredictable event, where the time of default is specified as a stochastic jump process.[7] Second, structural models build on Merton (1974) and Black-Scholes (1973) contributions.[8] Since structural models offer an economically intuitive framework to the pricing of credit risk, a large body of empirical literature has grown testing theoretical determinants of credit spreads with market data.[9] For example, within the structural framework, default is triggered when the leverage ratio approaches unity (i.e. debt equals total assets, thus, no equity is left). An increase in firm value is, thus, reducing the leverage and is, therefore, reducing the probability of default (and credit spreads). Similarly, according to the option pricing theory, owning a corporate bond is analogous to owning the firm's assets and giving a call option (with an exercise price equal to the amount of debt) on the assets to equity holders. It is clear that an increase in asset (i.e. firm) value is associated with lower probability of default and higher corporate bond values. On the other hand an increase in the firms' volatility increases the value for equity holders (i.e. value of the call option) at the expense of bondholders (i.e. increasing probability of default and lowering corporate bond values). We, therefore, test the following hypotheses:

H1: ASW spreads are negatively related to firms' value.

H2: ASW spreads are positively related to firms' volatility.

Firms' value and volatility, however, cannot be measured directly. For this reason, previous related studies use stock market returns and various volatility indices to proxy for the firms' value and volatility (Huang and Kong, 2003; Alexander and Kaeck, 2008; Aretz and Pope, 2012; Collin-Dufresne et al., 2001). When (past) realized stock market returns are higher (i.e. business climate is better), implied equity values (and, thus, also the firm value) are also higher. Higher firm values imply lower probability of default and higher recovery rates (Collin-Dufresne et al., 2001). The use of returns on stock market and volatility indexes in our study is further justified by the fact that we examine ASW spreads for corporate bond indexes rather than for individual bonds.

In addition to firm values and volatility, risk-free rate plays an important role in the structural models. The contingent claim (i.e. option pricing) framework for valuation of corporate securities is essentially a risk-neutral valuation. Since higher risk-free rates increase the risk-neutral drift they lower the probability of default (Merton, 1974). The lower probability of default narrows the credit spread and leads to a negative association of interest rates and credit spreads (Longstaff and Schwartz, 1995). The risk-free interest rate is, therefore, expected to be negatively related to default risk. Another argument supporting the inverse relationship between interest rates and credit spreads refers to the consideration of business cycles. For example, in periods of economic recessions when both interest rates and stock market returns tend to be lower, corporate defaults with low recovery rates tend to occur more often.

Early empirical papers use government bond yields as a proxy for the risk-free rate. Although swap interest rates are not completely free of risk they are often regarded as a better benchmark for the risk-free rate than government yields (Houweling and Vorst, 2005). For example, they do not suffer from temporary pikes sometimes caused by characteristics of repo agreements involving government bonds. Furthermore, swaps have no short sale constraints, are less influenced by regulatory or taxation issues, and tend not to be affected by scarcity premiums in times of shrinking budget austerity. Finally, swap rates closely correspond to the funding costs of market participants (see Houweling and Vorst, 2005, and Hull et al., 2004). Overall, we expect a negative association between ASW spreads and swap interest rates. Thus, we test the following hypothesis:

H3: ASW spreads are negatively related to swap interest rate level changes.

A further possible determinant of credit spreads is the difference between the swap interest rate and the interest rate on a par value government bond of the same maturity, known as the swap spread (Duffie and Singleton, 1999; Liu et al, 2006). More recently, Feldhütter and Lando (2008) decomposed the swap spread into a credit risk element, a convenience premium, and idiosyncratic risk factors. They concluded that the major determinant of swap spreads was the convenience yield defined as investors' willingness to pay a premium for the liquidity of government bonds. The importance of the convenience yield is especially apparent in unsettled markets. For example, dramatic events during the recent crisis altered investors' risk perception and consequently increased demand for more liquid assets, such as government bonds (so called flight to liquidity).[10] The higher demand inevitably resulted in higher prices and, thus, lower yields relative to other asset classes (see Aussenegg et al., 2013).[11]

Empirical evidence for the association of swap spreads and credit spreads is provided for several markets. For example, Brown et al. (2002) report a significant positive relationship between swap and credit spreads in the Australian market. Kobor et al. (2005) find a positive long-term relationship between swap spreads and credit spreads for US AA-rated bonds with maturities of two, five and ten years. Finally, Schlecker (2009) documents a cointegration relationship of credit spreads with swap spreads for the US as well as the European corporate bond markets. We, therefore, test the following hypothesis:

H4: ASW spreads are positively related to swap spreads.

3. Data and methodology

3.1 Data

Our sample consists of ASW spreads for 23 different iBoxx European Corporate Bond indexes, provided by Markit. The sample encompasses 10 industry indexes (Automobiles, Chemicals, Food and Beverages, Health Care, Oil and Gas, Personal and

Household Goods, Retail, Telecommunications, Utility, and Banks) and 13 composite indexes stratified by industry groupings (Corporates, Financials, Non-financials), regulatory considerations (Tier 1 Capital, Lower Tier 2 Capital), credit rating (from AAA to BBB) and seniority (Senior and Subordinated). In our analysis we focus on the period from January, 1st 2006 until January, 30th 2009, including 779 trading days.

Sample bond indexes are grouped based on the classification and strict criteria provided by Markit. For example, the market capitalization weighted iBoxx Benchmark indexes consist of liquid bonds with a minimum amount outstanding of at least €500 million and a minimum time to maturity of one year. Furthermore, the bonds need to have an investment grade rating and a fixed coupon rate. Bonds with embedded options, such as sinking funds and amortizing bonds, callable and undated bonds, floating rate notes, convertible bonds, bonds with conversion options, and collateralized debt obligations (CDOs), are all excluded from the iBoxx bond indexes.

Bond index values are calculated daily based on market prices, thus, they represent the most accurate and timely bond pricing available. More specifically, the asset swap spread $(ASW_{i,t})$ for each of the bonds included in the index is calculated based on the present value of fixed payoffs (PV_{Fixed}) and floating payoffs $(PV_{Floating})$ of a synthetic asset swap and the bond's dirty price (DP):[12]

$$ASW_{i,t} = (PV_{Fixed} - DP)/PV_{Floating} \tag{1}$$

The starting point in calculating the ASW spread is, therefore, distinguishing between the present value of fixed (PV_{Fixed}) and the present value of floating payments $(PV_{Floating})$:[13]

$$PV_{Fixed} = \sum_{t=1}^{T} C_t \cdot DF_t^{Fixed} + Principal_T \cdot DF_T^{Fixed} \tag{2}$$

$$PV_{Floating} = \sum_{t=1}^{T} (L_t/360) \cdot DF_t^{Floating} \quad (3)$$

C_t is the current coupon; L_t is number of days between floating rate payments; Discount factors for fixed (DF^{Fixed}) and floating rate ($DF^{Floating}$) payments are determined based on the Markit Swap curve.[14] The ASW spread for each of the sample 23 indexes *(ASW_t)* is then calculated as market value-weighted average of the *n* index constituents:

$$ASW_t = \sum_{i=1}^{n} ASW_{i,t} \cdot W_{i,t}^{MV} \quad (4)$$

where $W_{i,t}^{MV}$ is the (market value) weight of bond *i* on trading day *t*.

3.2 Sample descriptive statistics

Descriptive statistics of our sample of ASW spreads are provided in Table 1- Panel A. Financials and Non-financials are composite indexes that include bonds from respective sectors. Corporate Composite is a composite index and includes 1,082 corporate bonds that constitute all sample indexes. The average size of our bonds included in the Corporate Composite index amounts to €910.4 million. AAA-rated bonds have the highest volume with an average issue size of more than €1.3 billion. The notional amount of all bonds in our sample totals €985 billion by the end of January 2009.

***** Insert Table 1 about here *****

The mean ASW spread for the Corporate Composite Index is 87.8 basis points. The average time to maturity of all bonds included in this index amounts to 5.28 years.[15] The median daily change in ASW spreads is highest for Tier 1 Capital ASW spreads and lowest for Health Care and Telecommunication sectors. The values for the annualized standard deviation highlight significant time series variations. For the Tier 1 Capital sub-sample, for example, the annualized standard deviation is 2.4 times higher than for the Utility sector. Daily spread changes are highly leptokurtic for all sectors. The skewness of spreads is generally positive, with extreme values for Banks, Tier 1 Capital and AAA-rated corporate bonds.[16] These three sectors exhibit the highest level of (positive) skewness and excess-kurtosis.

Differences in median ASW daily spread changes, across credit ratings, are not significant. For example AA and BBB have the same median daily spread changes (see Table 1-Panel A). Absence of significant differences in median ASW spread changes across different ratings during the crisis period is in line with the results for the lack of differences in excess returns on iBoxx bond indexes reported in Aussenegg et al. (2013).[17] The differences between average (mean and median) ASW spread changes for senior and subordinated bonds are notable (see Table 1).

Figure 1 presents the co-movement of ASW spreads for ten different industry sectors. As expected, the ASW spreads for the financial sector dominate the spreads of all other industries. Other sectors with above-average spreads during the credit crisis (especially in the year 2008) are Oil & Gas as well as Automobiles & Parts. Overall, we observe a significant increase in levels, volatility and diversity of ASW spreads during the credit crisis.

***** Insert Figure 1 about here *****

The evolution of ASW spreads of the iBoxx Corporate Bond indexes and its determinants during the sample period is illustrated in Figure 2. The stock market was increasing steadily until summer of 2007. In the following 18 months, however, the European markets lost more than half of its value. The level of interest rates peaked in the summer of 2008. Since then the interest rates were declining until the end of our sample period. Volatility, swap spreads, as well as ASW spreads of the Corporate Composite bond index were relatively moderate until June 2007. Thereafter they all were increasing sharply with a notable jump in September 2008.

***** Insert Figure 2 about here *****

3.3 Markov switching model

The reported leptokurtic distribution of our sample ASW spreads together with time-varying properties of the parameters call for consideration of non-linearity and regime shifts. Markov models provide an intuitive way to model structural breaks and regime shifts in the data generating process.[18] Such models can be linear in each regime, but due to the stochastic nature of the regime shifts nonlinear dynamics are incorporated. The models define different regimes allowing for dynamic shifts of economic variables at any given point in time conditional on an unobservable state variable, s_t.[19] Another advantage of using a latent variable s_t is the constantly updated estimate of the conditional state probability of being in a particular state at a certain point in time. In our specification the state parameter s_t is assumed to follow a first-order, two-state Markov chain where the transition probabilities are assumed to be constant.

We estimate a two-state Markov model explaining ASW spread changes ($\Delta\mathrm{ASW}_{k,t}$), for each sector k:[20]

$$\begin{aligned}\Delta\mathrm{ASW}_{\mathrm{k,t}} = {} & \beta_{S,k,0} + \beta_{S,k,1}\Delta\mathrm{ASW}_{\mathrm{k,t-1}} + \beta_{S,k,2}\text{Stock return}_{k,t} + \beta_{S,k,3}\Delta\mathrm{VStoxx_t} \\ & + \beta_{S,k,4}\Delta\text{IR\_Level}_t + \beta_{S,k,5}\Delta\text{Swap Spread}_t + \varepsilon_{S,k,t} \qquad (5)\end{aligned}$$

The dependent variable, $\Delta \text{ASW}_{k,t}$, is the change (rather than level) in the ASW spread of industry sector k on day t.[21] $\beta_{S,k,j}$ is a matrix of j regression coefficients as used in model of the k^{th} sector, which is dependent on the state parameter s. $\Delta \text{ASW}_{k,t-1}$ is the one period lagged ASW spread change. The inclusion of lagged spread changes ($\Delta \text{ASW}_{k,t-1}$) as control variable is motivated by both previous studies and properties of our sample.[22]

Equity values ($\text{Stock return}_{k,t}$) are proxied by respective Dow Jones (DJ) Euro Stoxx indexes which are also provided by Markit (see Table 1).[23] The VStoxx index (ΔVStoxx_t) is used as a proxy for the implied volatility, since it is the reference measure for the volatility in European markets.[24]

The change in the level of interest rates is estimated by Principal Component Analysis (PCA) using Euro swap rates with maturities between one and ten years (i.e. 10 maturity brackets).[25] PCA allows us to use the entire term structure of interest rates and, thus, avoids an arbitrary selection of a point from the yield curve.[26] Since the input to the PCA must be stationary, we use the first difference of interest rate swap rates.[27] As a result, the PC themselves are stationary and can be directly used in our regressions without using first differences.

In the PCA context, swap rate maturities represent key liquidity points. The PCA uses historical shifts in the swap rates to compute the correlation matrix of the shifts. The matrix is then used to compute eigenvectors and eigenvalues. The first eigenvector corresponds to a level and the second to a slope of the swap rate curve shift. The computed eigenvalues are in fact weights, which tell us the relative importance of the level and slope shifts. The resulting first principal component of our analysis ($\Delta \text{IR\_Level}_t$), therefore, reveals the changes in the level of the entire swap rate curve. Specifically, in our study, the first PC (the variable $\Delta \text{IR\_Level}_t$ used in equation (5)) explains 92.7% of interest rate level changes.

The swap spread, as a proxy for bond market liquidity, is measured as the difference between the five year European swap interest rate and the yield of German government bonds of the same maturity.[28] ΔSwap Spread$_t$ in equation (5) represents daily changes in the Swap spread. $\varepsilon_{S,k,t}$ is a vector of disturbance terms, assumed to be normal with state-dependent variance $\sigma^2_{S,k,t}$. Descriptive statistics for all explanatory variables, together with expected signs of the coefficients in equation 5, are presented in Table 1 – Panel B.

4. Results

4.1 Determinants of ASW spreads in different market regimes

Results of the Markov switching regressions are provided in Table 2. As expected, the results suggest that regimes affect the intercept, coefficients, and the volatility of the process. The majority of all sectors exhibit a negative autocorrelation during the second (low volatility, therefore, calm) regime and a positive autocorrelation in times of high volatility (turbulent regime), indicating that the data generating process consists of a mixture of different distributions. The positive autocorrelation effect in the more volatile regime is particularly pronounced for Automobile & Parts, AAA-rated Corporates, as well as for finance related indexes. The residual volatility (Std. Dev.) is higher during turbulent than during calm market periods for all sample sectors. On average, the residual volatility is 5.4 times higher during the turbulent periods, ranging from five (e.g. Chemicals, Utilities, Telecommunications) to seven (Tier 1 Capital) times. Finally, the remaining estimated coefficients differ considerably between the two market regimes.

***** Insert Table 2 about here *****

Stock market returns are not significantly related to ASW spread changes of the non-financial sector index, neither in turbulent nor in the calm regimes. There are, however, some important industry differences within the Non-financial sector. For example, Food and Beverages as well as Utilities exhibit a negative association between credit spreads and stock market returns in both regimes, as predicted by structural models (hypothesis 1). In the regressions for the Financials composite index, the stock market return coefficients are negative (and statistically significant at the 5% level or better) only during calm periods. This is further confirmed by the negative and highly statistically significant coefficients in regressions for Subordinated Financials, Banks, and Lower Tier 2 Capital indexes. For these indexes, increasing stock returns in calm periods are strongly associated with lower ASW spreads.

Furthermore, the VStoxx is not significantly related to ASW spreads of Financial and Non-financial indexes, both in calm as well as turbulent periods (hypothesis 2). There is, however, evidence that volatility positively influences ASW spreads especially in the turbulent regime.[29] For example, in all but 1 out of 23 regressions the coefficient for volatility is positive, and in 10 out of 22 regressions significant at the 5% level or better. Notably, for three indexes (Food and Beverages, Banks, and Financial Subordinates) we report a negative and statistically significant association between volatility and credit spreads during calm periods.[30] The negative and statistically significant relation between volatility and credit spreads during calm periods is also observed for the Corporates Composite index, in almost all credit rating (Corporates AAA, Corporates A and Corporates BBB) and seniority classes (Corporates Senior and Corporate Subordinate). The reported negative association of the ASW spreads and stock market volatility during calm periods is consistent with Alexander and Keack (2008) who report a negative association of CDS spreads and volatility in calm regime for Non-financials (statistically significant at the 5% level) and Financial senior sectors (not statistically significant). Cremers et al. (2008) also report a significantly negative impact of implied market volatility on credit spreads of 69 US firms**.** Overall, the results suggests that credit spreads tend to be more affected by stock market returns during calm periods while in turbulent periods stock market volatility becomes a more important determinant of credit spreads.

Interest rate level changes ($\Delta\text{IR\_Level}_t$) affects ASW spreads negatively in both regimes (hypothesis 3).[31] Table 2 also reveals larger negative coefficients for interest rate level changes ($\Delta\text{IR\_Level}_t$) in turbulent compared to calm regimes. Thus, decreasing interest rates in turbulent periods tend to increase spreads more than in calm periods. This result contradicts findings for CDS spreads reported by Alexander and Kaeck (2008) who report a negative and statistically significant relation between interest rates and credit spreads only during calm periods. In addition, they report lack of statistically significant relation between interest rates and credit spreads for financial indexes (Financial senior and Financial subordinate).[32]

Finally, the influence of swap spreads ($\Delta\text{Swap Spread}_t$) is positive, with extremely large coefficients, in all regressions during turbulent periods (hypothesis 4). In 16 out of 23 cases the positive coefficients are significant at the 5% level, or better. The swap spreads, however, do not have a strong effect on credit spreads during calm periods. For example, none of the 19 coefficients for $\Delta\text{Swap Spread}_t$ (with a positive sign) are statistically significant in calm periods. This evidence is in line with our prediction that the liquidity premium plays a particularly important role in turbulent periods.

The reported high probabilities of staying in respective regimes suggest significant market persistency. The persistency tends to be higher for calm regimes. For example, once in a calm regime Financials have a probability of 95% of remaining in the calm regime. The corresponding probability for the turbulent regime is 92%. The respective probabilities for

Non-financials indexes are 97% and 92%, respectively. The above results are consistent with reported longer state durations for calm compared to turbulent periods. For example, for Financials indexes the estimated duration of calm periods is 19 days compared to 13 days for turbulent periods. The corresponding values for Non-Financials indexes are 31 and 12 days, respectively.

4.2 Regime specific moments of ASW spread

Regime specific moments of ASW spread changes ($\Delta \text{ASW}_{k,t}$) are presented in Table 3. The first column of Table 3 presents the length of time (in percentage terms) with characteristics of the high volatility regime. The mean values for non-financial and financial sectors are 26.8% and 39.3%, respectively. As expected, mean $\Delta \text{ASW}_{k,t}$ are significantly lower in the calm than in the turbulent regime. The reported positive skewness, for all sectors, suggests that the balk of the changes lie to the left of the mean in both regimes (an exception is the Oil and the Gas sector in the turbulent regime). Spread changes in the calm regime are closer to normality with an average change of 0.10 basis points, an average skewness of 0.44 and an average excess kurtosis of 0.64 (for Corporate Composite index). The respective values are very different during turbulent periods. For example, average daily spread changes are 1.19 basis points, the average skewness is 0.87, and the average excess kurtosis is 2.29 (for Corporate Composite index). Notable, the distribution of ASW spread changes of AAA-rated Corporates and Banks is highly leptokurtic with an excess kurtosis of 6.75 and 13.2, respectively, whereas the excess kurtosis for Retail sector is the lowest in the sample.

***** Insert Table 3 about here *****

Overall, our findings confirm that ASW spread changes deviate much more from normal distribution in the turbulent regime.

4.3 Equality of coefficients in different market regimes

Engel and Hamilton (1990) suggest a classical log likelihood ratio test with the null hypothesis (H_0) of no switching in the coefficients ($\beta_{S_t=1}$ and $\beta_{S_t=2}$) but allow for switching in the residual variance ($\sigma_{S_t=1}$ and $\sigma_{S_t=2}$).[33] Thus we test the following hypothesis:

$$H_0 : \beta_{S_t=1,j} = \beta_{S_t=2,j} \text{ for all } j, \; \sigma_{S_t=1} \neq \sigma_{S_t=2} \tag{6}$$

The corresponding results are reported in Table 4.

***** Insert Table 4 about here *****

The null hypothesis of equal coefficients in both regimes can be rejected for all 23 sectors at the 5% level. Overall, indexes for financial industry provide most evidence of regime switching.[34] This contradicts findings documented in Alexander and Kaeck (2008), reporting no evidence of switching in at least one of the coefficients in the Financial Senior index. The above specification test could be affected by a high degree of correlation between explanatory variables. In our sample the two variables with the highest correlation are the equity market variables (i.e. stock returns and ΔVStoxx). Our (unreported) results for the Markov switching models with only one of the two stock market variables remain robust.[35] The switching, however, is more pronounced in the model with stock market volatility (LR test statistically significant in 21 out of 23 indexes) than in the model with stock returns (LR test statistically significant in 17 out of 23 indexes).

We further conduct a test for switching in each explanatory variable of model 1 (see Table 5). As expected, for the stock market volatility the hypothesis of no switching can be rejected for 22 out of 23 indexes (at the 5% level). Evidence for switching in other explanatory variables varies across industries. For example, Automobiles & Parts, Chemicals, Personal & Household Goods, and Utility do not exhibit regime switching neither in the stock market returns nor in swap spreads. Instead, these sectors are more likely to experience regime switching in interest rates.[36] Automobiles & Parts, Oil & Gas, and Banks are the only industry sectors that exhibit strong regime switching in the coefficient for lagged dependent variable. The above results provide further evidence for different time varying behavior of ASW spreads across different industries.

***** Insert Table 5 about here *****

4.4 Tested-down Markov model

After clearly providing evidence of switching in the variables in most of the industry indexes we tested the Markov model down in the following way. First, we run the model with all variables (as in Table 2). Second, we perform a series of constrained estimates of the model by fixing the most insignificant coefficient at zero (i.e. we start with 10 (5x2) coefficients and reduce the model step by step). This procedure is repeated until all (remaining) coefficients are statistically significant. The final estimate (i.e. the last one in the series of constrained estimates) is than presented in Table 6.[37]

The results further highlight industry variations. For example, Automobiles & Part, most financial indexes and AAA Corporates exhibit positive autocorrelation in turbulent and negative in calm periods. On the other hand, Health Care, Personal & Household Goods, and

Utilities exhibit significant negative autocorrelation in both regimes, with very similar coefficients. Whilst stock market returns tend to be the main determinant during calm periods, stock market volatility tends to be the key determinant during turbulent periods. Swap spreads appear to be an excellent proxy for bond market liquidity, since it is highly significant in turbulent periods and not significant during calm periods. Interest rates are an important determinant of ASW spreads in both regimes and in all sectors (except Retail and Health Care).[38] Notably, interest rates remain an important determinant of ASW spreads in the financial sector in both regimes.

***** Insert Table 6 about here *****

Our findings suggest significant differences in the importance of regimes across various industries. For example, the results for the Banking sector are very much different from the results for Utilities. Whilst differences in estimates across regimes are very different in Banking, they are not significant for Utilities. Our findings also suggest significant differences in the importance of stock market returns, changes in volatility and changes in interest rates for explaining ASW spreads from various industries. For example, ASW spreads in the Utility sector are not significantly affected by equity volatility in any of the regimes. On contrary, ASW spreads in all other industries are significantly affected by equity volatility during turbulent regimes.

There are also significant differences in the results across credit ratings. For example, the autocorrelation is more significant (in both regimes) for AAA bond indexes than for BBB indexes. This is also the case for the differences in determinants of ASW spreads for senior and subordinated bonds. For example, we report different autocorrelations and the effect of stock market returns and interest rates for these two sub indexes, in different market regimes.

5. Economic identification of regimes and drivers of regime changes

5.1 Economic identification of regimes

So far we defined the turbulent and calm regimes based on statistical procedures and resulting differences in coefficients, residuals' volatility, probability of staying in the respective regime, state duration and ASW spreads' regime specific moments. It is important to investigate to what extent our model estimates correspond to economic events and whether the turbulent regime indeed relates to the events from the recent financial crisis.

In the presence of regime switching, we expect a positive relation between volatility of ASW spread changes and filtered probabilities of entering into a turbulent period. Furthermore, we expect that the filtered probabilities relate to dates of major events during our sample period. We, therefore, plot the major events together with estimated probabilities and squared ASW spread changes (see Figure 3). In this way we undertake economic identification of regimes identified by our Markov model (equation 5).

The selected events are: (1) first reports on a sharp drop in US house prices, (2) the Ameriquest crisis, (3) financial markets rallied to a five year high, (4) the credit markets crisis, (5) LIBOR rose to 6.79%; (6) the collapse of Bear Stearns, (7) the nationalisation of Freddie Mac and Fannie Mae, (8) the collapse of Lehman Brothers, and (9) the Citigroup crisis. The above events reflect the fact that the recent credit crisis originated in the US housing and mortgage markets and then spread to Europe and beyond.[39]

***** Insert Figure 3 about here *****

Figure 3 depicts a positive association between probabilities and ASW spread volatility and shows the consistency with the selected events. As expected, the spikes marking an increase in ASW volatility (black line) correspond to high probabilities of entering into a turbulent period (grey line). For example, the US housing bubble bursted when housing prices started to flatten and eventually dropped in the first quarter of 2006 (see event 1 in Figure 3). Consequently, the first three months of our sample period exhibit high volatility together with a high probability of entering into a turbulent period. The financial crisis escalated as Ameriquest Mortgage revealed plans to close its retail branches and announced significant job cuts in May 2006 (see event 2 in Figure 3). In November 2006 markets rallied to a five year high leading to an ASW spread reduction of 7 basis points (see event 3 in Figure 3). Another volatile period started when credit markets froze in summer 2007. In a coordinated move with the Federal Reserve, the European Central Bank injected €95 billion into the European banking systems (see event 4 in Figure 3). At the end of August 2007 Ameriquest Mortgage finally went out of business. On September 4th, 2007, LIBOR rates rose to 6.79%, the highest level since 1998 (see event 5 in Figure 3). During the following four months ASW spreads returned to the calm regime lasting until the stock market downturn in January 2008. Bear Stearns (at that time the fifth largest investment bank in the world) was on the verge of collapse before it was sold to rival JP Morgan on March 16th, 2008 (see event 6 in Figure 3). The takeover was marked by the jump in the Corporate Composite ASW spread of 33 basis points within the first 11 trading days in March 2008 (with a maximum daily change of 19.15 basis points). For the following five months, our sample entered the volatile regime only occasionally. During this period Indymac Bank was placed into receivership by the Office of Thrift Supervision.

As indicated by the estimated probabilities, from August 2008 we basically remain in the turbulent regime until the end of our sample period. Freddie Mac and Fannie Mae were nationalized at the beginning of September 2008 (see event 7 in Figure 3). Around the same time rumors about liquidity problems of Lehman Brothers surfaced and Lehman filed for bankruptcy protection on September 15th, 2008. This event marks the peak of the financial crisis (see event 8 in Figure 3). For example, within 23 trading days the Corporate Composite ASW spread exploded by 144 basis points. The highest single day jump (of 17.4 points) was on September 16th, 2008. Days later it became public that AIG was on the brink of bankruptcy, causing the ASW spread to increase nearly 16 basis points within a day. The last and largest spike in our sample credit spreads occurred on November 21st, 2008. Due to liquidity problems of Citigroup (see event 9 in Figure 3), the value of the Corporate Composite ASW spread jumped by 20.06 basis points. The market capitalization of the once biggest bank in the world dropped by 60% within a week. Finally, the US government agreed to invest several billion dollars and save the system-relevant financial institution. The remaining trading days in our sample exhibit a high level of volatility as the downturn on financial markets continued.

Overall, the estimation results presented in Figure 3, provide robust conclusion that our turbulent regime is indeed related to the events from the recent financial crisis.

5.2 Determinants of regime changes

Having demonstrated significant regime changes we now examine main drivers of the regime changes. To statistically test variables that induce a regime shift, we estimate a logit model relating the estimated state probability of being in either of the regimes to structural variables. The dependent variable is, therefore, equal to one if the estimated probability from equation (5) is higher than 0.5 (indicating a high volatility - turbulent regime) and equal to zero if the estimated probability value is equal to or lower than 0.5 (indicating a low volatility - calm regime). The explanatory variables are the same structural variables as in equation (5), with an addition of the squared change of lagged ASW spreads ($\Delta \mathrm{ASW}_{t-1}^{2}$). Given that volatility of ASW spreads is expected to be high during turbulent regimes (i.e. when volatility of residuals is high) it is important to examine the causality between regime changes and the volatility of ASW spreads (proxied by $\Delta \mathrm{ASW}_{t-1}^2$). The model, thus, has the following form:[40]

$$P_t = P[y_t = 1] = \frac{1}{1+e^{-(\alpha_0+\alpha_1 x_{t-1})}}, \quad (7)$$

Where $P_t[y_t = 1]$ denotes the filtered probability of being in the high volatile regime at time t and α_0 and α_1 represent regression coefficients. Various models are estimated using only one lagged explanatory variable x_{t-1} at a time.

The $\Delta \mathrm{ASW}_{t-1}^2$ column in Table 7 reveals that large changes in the volatility of credit spreads, irrespective of the direction, lead to a shift in market regimes.[41] The coefficients are statistically significant at the 5% or better in 18 (of 23) regressions. Results presented in the second column in Table 4 show that lagged changes of credit spreads ($\Delta \mathrm{ASW}_{t-1}$) have a significant and positive influence on the regime probability (the coefficients are statistically significant at the 5% or better in 21 (of 23) regressions). As expected, stock market returns have a negative sign in all sectors (statistically significant in 8 cases), indicating that positive daily market returns reduce the probability of switching to the high volatility regime. In contrast, lagged changes in volatility ($\Delta \mathrm{VStoxx}_{t-1}$) do not seem to have any influence on the switching behavior. The level of interest rates (ΔIR_Level), on the other hand, is negatively associated with credit spreads in all sectors (but statistically significant only in 3 cases). The coefficients for the lagged swap spreads are not statistically significant.

***** Insert Table 7 about here *****

Overall, our results identify historical levels and volatility of ASW spreads together with stock returns and interest rates as the major drivers of regime shifts. It is worth noting that structural variables that drive ASW spreads from one regime to another vary across industries. For example, whilst interest rates force regime changes for Automobiles & Parts, Telecommunications, and Corporates AAA, stock market returns force regime changes for Personal & Household Goods and Banks. The above results differ from Alexander and Kaeck (2008) who identified interest rates as the only structural variable that drives CDS spreads' regime changes.

6. Robustness checks

In this section we conduct further analysis and examine the robustness of our findings. First, we conduct in and out-of-sample tests for accuracy of our model's predictions. Second we repeated tests, for determinants of ASW spreads and regime changes, in an extended sample to include a most recent, post-crisis, period.

6.1 In and out of sample accuracy tests of the Markov switching model

In this section we address two important issues. First, we examine in and out of sample accuracy of our Markov model, thus, answering the question to what extent our regime-switching model describes credit spreads during the recent financial crisis. Second, we examine the accuracy relative to an equivalent OLS model. By comparing estimates of our regime-switching model with the equivalent OLS model we further highlight importance of distinguishing between market regimes in certain industries.[42]

6.1.1 In sample accuracy test

First, we use the Markov and the OLS models to predict changes in ASW spreads. The predictions for the Markov model are based on the estimated parameters (reported in Table 2) for calm and turbulent regimes. The turbulent and calm regimes were defined using probabilities estimated by our Markov model. Observations with the estimated probabilities above 0.5 were included in the turbulent regime. The predictions for the OLS model are based on the estimated parameters for the entire sample period. The predictions for the two regimes are, therefore, based on the same OLS parameters. Second, we regress the actual changes of the sample ASW spreads against the predicted changes obtained by the respective models. We therefore have two regressions for each of the regimes. Intercepts close to 0 and the slope coefficients close to 1 are an indication of a better model accuracy.

The results for selected industry sectors are presented in Table 8.[43] In the turbulent regime, Oil and Gas and Telecommunication sectors have the highest R^2 and F statistics. The hypothesis that the coefficient slope equals to 1 cannot be rejected in OLS regressions for Oil and Gas and Markov regressions for Oil and Gas and Telecommunication sectors. The hypothesis that the intercept is equal to 0 cannot be rejected only in regressions for Oil and Gas sector. The models, therefore, work particularly well for Oil and Gas sector.

***** Insert Table 8 about here *****

In the calm regime, the hypothesis that the slope coefficient equals to 1 has to be rejected for all sectors. Notably, the t-statistics for the slope coefficients in the calm period are much higher compared to the turbulent regime. The hypothesis that the intercept term equals to 0 has to be rejected only in Retail (OLS model) and Banking (OLS and Markov models) sectors.

6.1.2 Out of sample accuracy test

The predictions for the out of sample test are based on our Markov model (equation 5) for the two regimes and an equivalent OLS model using a rolling window of 500 (past) daily observations. The first estimation window starts on January 6th, 2006 and ends on December 18th, 2007 (500 observation). The out-of-sample period contains 278 observations (trading days), from December 19th, 2007 until January 29th, 2009. We than use the predictions to test the null hypothesis that the mean difference between actual and predicted changes in ASW spreads are zero in different regimes.[44] The results are presented in Table 9.

***** Insert Table 9 about here *****

In the calm regime, the difference between average (mean) actual and predicted ASW spread changes is not statistically significant across selected sectors and for both models. In the turbulent regime, the (absolute) mean difference between actual and predicted ASW spread changes is smaller for the Markov model compared to the OLS model in all sectors, depart from Oil & Gas. Thus, the Markov model estimates are (in most cases) closer to the actual ASW spread changes. When the OLS model is used the mean difference between actual and predicted ASW spread changes is statistically significant for Banking, Telecommunication, and the Composite sectors. In contrast, when the Markov model is used for predictions, the corresponding differences are not statistically significant in any of the sectors.

Overall, our Markov model, based on variables identified by the structural model of credit risk, exhibits better in and out of sample accuracy compared to the equivalent OLS model for determinants of ASW spreads.

6.2 Post-crisis period

In this paper we examine the period dominated by the severe financial crisis. We now check for the robustness of our results in an extended sample that includes a most recent, post-crisis period.[45] Overall (unreported) results for the extended sample (January 2006-October 2013) are economically and statistically consistent with our results for the crisis period (January 2006-January 2009).[46] For example, signs and significance of coefficients (Stock returns, ΔVStoxx, ΔIR_Level and ΔSwap spreads) are very similar. The new coefficients for the autocorrelation factor (ASW_{t-1}) are predominantly positive, thus, economically and statistically consistent, with our earlier estimates, only in turbulent periods. During calm periods, the coefficients are no longer predominantly negative (and significant). Instead, they are now predominantly positive. We explain the above results with prolonged uncertainty regarding the length and scale of the recent financial crisis, and, therefore, credit risk. The crisis period was characterized by several major events each of which was associated with peaks in ASW spreads (see Figure 3). The calm periods were, therefore, associated with the reversal of expectations in the aftermath of major market events, thus, resulting in negative autocorrelation. During the extended sample period (2006-2013), the sharp reversal effect was diluted because of (relatively) fewer major market events. Consequently, the autocorrelation is predominantly positive both in turbulent and calm periods.

In the extended sample, lagged ΔASW^2 remains the dominant driver of regime shifts with (always) positive and statistically significant coefficients.[47] Past ASW spreads changes are (statistically) still a very important determinants whilst past Stock returns remain less important driver of regime shifts. The other three variables (lagged ΔVStoxx, lagged ΔIR_Level and lagged ΔSwap spread) are, as previously reported, not statistically significant.

7. Conclusion

In this study we examine the time-series dynamic of credit risk based on ASW spread data for a set of 23 European iBoxx Corporate Bond indexes during the period from January, 1st 2006 to January, 30th 2009. Our results suggest a leptokurtic distribution for the sample ASW spreads characterized by huge excess kurtosis. To allow for dynamic shifts in the data generating process, we employ a two-state Markov model. The corresponding results reveal that the estimated coefficients differ considerably between the two regimes. For example, stock market returns are negative and in most cases significantly associated with ASW spreads in calm periods. This result also holds in turbulent periods but to a lesser extent. The stock market volatility has a positive effect on ASW spreads in turbulent periods, whereas the opposite is true in calm periods. As predicted, a higher swap spread, which can be considered as a quality premium required for non-government bonds demands larger ASW spreads. However, this only holds in turbulent regimes. In calm periods, the relationship is not statistically significant. Independent of the regime, the level of interest rates is clearly negatively related to credit risk. The lower interest rates, therefore, lead to an increase in ASW spreads.

Our findings suggest significant differences in the importance of stock market returns, volatility, and interest rates for explaining ASW spreads from various industries. This result is surprising since theory predicts that all credit spreads should be affected by those variables (Collin-Dufresne 2001) and empirical evidence document considerable comovement of credit spreads derived from bond index portfolios (Pedrosa and Roll, 1998) of various industries. The above results highlight further our funding that ASW spreads exhibit regime dependent behavior, especially in the financial sector. We identify market liquidity factor as one of the important systematic components outside structural models, especially in turbulent periods.[48] The regime transitions between turbulent and calm regimes are mainly driven by lagged ASW levels, lagged ASW spread volatility, and stock returns. On the other hand, stock market volatility, interest rate levels and swap spreads are not important drivers of regime shifts. Our results differ from the results reported in studies on determinants of CDS spreads which identify interest rates as the only driver of the regime changes for CDS spreads (e.g. Alexander and Kaeck, 2008).

Our regime-switching model provides estimates that match well with economic events during the recent crisis. The model estimates are also robust in the extended sample that includes a post crisis period. The documented regime specific dynamics of ASW spreads is important for participants in the bond market, both for valuation and hedging purposes. Notably, the Markov switching model exhibits better accuracy compared to the equivalent OLS model in a number of industry sectors. For efficient hedging of credit risk market participants should, therefore, take into account differences between relevant market regimes and industry sectors. The regime shifts may also be important for investors in exchange traded funds (ETFs) that track bond indexes for different industry sectors.

Notes

[1] In the US, ASW are better known as Bond Total Return Swaps (TRS) or Bond Total Rate of Return Swaps (TROR).

[2] CDS are essentially insurance contracts where buyers agree to pay a predefined periodic fee (i.e. CDS spread) while the sellers provide compensation in case of a default.

[3] Theoretically, the difference between CDS and ASW spread (i.e. basis) is expected to be close to 0. In practice, however, the prices are different due to the impact of supply and demand and the fact that ASW spreads also reflect funding costs (see Chaudry, 2004). Other drivers of the basis are related to CDS counterparty risk, 'soft' credit events, and the inclusion of CDT options in CDS contracts (for more see Francis et al., 2003; Blanco et al., 2005; Merrill Lynch, 2003).

[4] Ang and Timmermann (2011; p. 19).

[5] For example, equity volatility seems to be driven by industry (rather than global) factors during calm periods (Aretz and Pope, 2012).

[6] Low liquidity remains a big limitation of the CDS market in the post-crisis period. For example, more than 31,000 out of 32,511 public firms included in Kamakura Risk Information Services had zero weekly non-dealer CDS trading volumes during the period 16th July 2010 to 28th June 2013 (i.e. 155 weeks). In other words, 69.7% of the reference names had 1 or fewer non-dealer contracts traded per day (Van Deventer, 2013). Dealer-end user trades represent only c. 25% of all trades in the single name CDS market. Dealer-dealer trades (as opposed to dealer-end user trades) represent c. 75% of trades in the single name CDS market. These trades are normally completed via inter-dealer brokers. Inter-dealer brokers do not take any proprietary positions but only match dealer orders. Data providers should therefore make appropriate disclaimers when quoting CDS prices, many of which are quotes not trades (Van Deventer, 2013). Financials represented 30% of the overall net notional and 32% of overall CDS weekly traded volumes (as on 1st July 2011). At the same time, the share in

overall CDS traded volume for names in Health Care, Oil and Gas, Utilities, Telecommunications was 0%, 2%, 3%, and 8%, respectively. As of 1st July 2011 (Credit Suisse, 2011; p. 2).

[7] For a detailed description of several well known reduced-form models see Duffie and Singleton (1999) and Hull and White (2000).

[8] Both Merton and Black-Scholes models consider corporate liabilities as contingent claims and are, therefore, entirely consistent: "Merton also developed the Black-Scholes model, and Black and Scholes had the valuation of corporate liabilities as part of the title of their original paper. But the risk structure of interest rates for zero-coupon debt and the extensions to coupon paying debt are in Merton (1974)." (Lando, 2004, page 54-55).

[9] See Huang and Kong (2003), King and Khang (2002), Duffee (1998), Collin-Dufresne et al. (2001), Elton et al. (2001) and Longstaff et al. (2005).

[10] See Longstaff (2004).

[11] This scenario is also in line with previous crisis. For example, Russian debt moratorium in 1998 resulted in market-wide reduction in liquidity which then led to an increase in both liquidity and default risk premiums (see Acharya et al., 2010 and BIS, 1999).

[12] For more on the calculation of Markit iBoxx indexes see Markit (2012; 2013).

[13] Based on the frequency of a bond's fixed rate payments, the floating-rate payment frequency is determined as follows: fixed rate paid yearly = floating rate paid semi annually; fixed rate paid semi annually = floating rate paid quarterly; fixed rate paid quarterly = floating rate paid monthly; else: fixed frequency = floating frequency (Markit, 2013).

[14] Markit SWAP curve is constructed from Libor rates and ICAP swap rates. The curve is interpolated to account for fixed and floating payoffs dates. For more see Markit (2013).

[15] Given that most liquid CDS spreads have 5-year maturity we can compare our results directly to the results reported in previous studies based on CDS spreads (e.g. Alexander and Kaeck, 2008).

[16]It is worth mentioning that the Corporates AAA index contains only one non-financial bond (issued by health care company Johnson & Johnson). The remaining 35 bonds in this index represent debt raised by highly rated financial institutions. Tier 1 Capital consists of the most subordinated bonds issued by banks.

[17] The results are also in line with anecdotal evidence for poor performance of credit rating agencies during the recent crisis.

[18] "Regime switching models parsimoniously capture stylized behavior of many financial return series including fat tails, persistently occurring periods of turbulence followed by periods of low volatility (ARCH effects), skewness and time-varying correlations. By appropriately mixing conditional normal (or other types of) distributions, large amounts of non-linear effects can be generated. Even when the true model is unknown, regime switching models can provide a good approximation for more complicated processes driving security returns … another attractive feature of regime switching models is that they are able to capture nonlinear stylized dynamics of asset returns in a framework based on linear specifications, or conditionally normal or log-normal distributions, within a regime. This makes asset pricing under regime switching analytically tractable." (Ang and Timmermann, 2011; page 1-2).

[19] For various applications of Markov switching models related to interest rates, bond markets, and credit risk modeling, see Clarida et al. (2006), Brooks and Persand (2001), Eyigunor (2006), Lando (2004) and Dionne et al. (2007).

[20] Our estimation procedure is based on iterative algorithm, similar to a Kalman filter (see Hamilton, 1989 and Alexander and Kaeck, 2008).

[21] Collin-Dufresne et al. (2001) and Alexander and Kaeck (2008) also examine credit spread changes. Studies that do not examine time series variation in spreads and their determinants use credit spread levels as dependent variables in respective models (see Tsuji, 2005; Cremers et al. 2008; Zhang et al. 2009; Cao et al. 2010). Models for levels tend to provide higher explanatory power measured by R^2. For example, Zhang et al. (2009) report R^2s up to 73% in models for levels compared to R^2s up to 5.4% in respective models for changes in CDS spreads.

[22] For example, Byström (2006) and Alexander and Kaeck (2008) report a high degree of autocorrelation in daily changes of CDS iTraxx index spreads, for all industry sectors. Our unreported results suggest that 15 of the 23 sample ASW spreads exhibit a highly significant degree of autocorrelation with mixed signs.

[23] The variable Stock $\text{return}_{k,t}$ is defined as the return of stock market index k from trading day $t\text{-}1$ to trading day t, calculated as: $Stock\ return_{k,t} = ln\left(\frac{Stock\ market\ index_{k,t}}{Stock\ market\ index_{k,t-1}}\right)$. Different stock market indexes are used for the 23 ASW indexes analysed in this study. The respective stock market index for every ASW index is reported in the last column of Table 1. These are the corresponding DJ Euro Stoxx sector indexes (except for the group of non-financial firms where the FTSE World Europe ex Financials index is used) and the DJ Euro Stoxx 600 index (Stoxx 600).

[24] The variable $\Delta VStoxx_t$ is defined as the difference between the VStoxx on trading day t and the VStoxx on trading day $t\text{-}1$, calculated as: $\Delta VStoxx_t = VStoxx_t - VStoxx_{t-1}.$ The use of implied rather than historical volatility

is justified by the results of previous empirical studies on credit spreads. For example, Cao et al. (2010) find that stock option implied volatilities explain CDS spreads better than historical volatilities. Similarly, Cremers et al. (2008) show that implied volatilities improve on historical volatilities when explaining variations of corporate bond spreads.

[25] Principal component analysis is originally developed by Spearman (1904). It is a non-parametric method that helps to reveal the underlying variance driving structure of a panel of data and extracts the most important uncorrelated sources of information.

[26] A typical example would be the arbitrary choice of a 5-year Benchmark Treasury Rate to proxy for the level of the term structure. For more on the importance of consideration of the entire interest rate term structure and the use of PCA in this context see (Litterman and Scheinkman, 1991; Dullmann et al., 2000; Aussenegg et al., 2013).

[27] Differences are defined as, Swap $\text{rate}_{n,t}$ – Swap $\text{rate}_{n,t-1}$ where *n* represents a particular maturity (in our case 1, … , 10 years).

[28] Time series of swap interest rates and government bond yields are from Datastream. For an alternative proxy for swap spreads see Lekkos and Millas, 2011.

[29] Our results are in line with Alexander and Kaeck (2008) and Naifar (2011), who report similar results for changes in iTraxx CDS spread indexes.

[30] It is worth noting that for the above mentioned indexes we report a positive association between volatility and credit spreads during turbulent periods.

[31] $\Delta\text{IR\_Level}_t$ affects ASW spreads negatively in 45 out of 46 cases. In 31 of the 45 cases the effect is statistically significant at the 5% level, or better.

[32] According to authors, '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' (p.1016). It is worth noting that Alexander and Kaeck (2008) sample period ends before the recent credit crisis.

[33] The likelihood ratio is asymptotically $\chi^2_{(5)}$ distributed.

[34] The Tier 1 Capital sector has the highest LR-statistic.

[35] Results are available upon request.

[36] Automobiles & Parts and Chemicals at the 10% significance level. Personal & Household Goods and Utility at the 5% significance level.

[37] Alexander and Kaeck (2008) tested their model down in a similar fashion (see page 1018).

[38] For Health Care interest rates are statistically significant only in turbulent period whilst for Retail only in calm period.

[39] By the end of 2006, 75% of all US subprime mortgages had been securitized and sold worldwide (Demyanyk and Van Hemert, 2009).

[40] The model is adopted from Clarida et al. (2006) and Alexander and Kaeck (2008).

[41] This is consistent with Alexander and Kaeck (2008) results for iTraxx Europe CDS spreads.

[42] It is worth noting that our analysis does not intend to formally test our Markov model against its OLS alternative. For a formal statistical test of a Markov switching model against its OLS alternative, see Alexander and Kaeck (2008).

[43] For brevity we present the results for five sectors. The results for other sectors are available upon request.

[44] The turbulent and calm regimes are defined using probabilities estimated by the Markov model.

[45] We are grateful to an anonymous referee for this suggestion.

[46] The results are available from authors upon request.

[47] Estimates with lagged squared changes in spreads also exhibit the highest R^2s.

[48] This finding is in line with Duffie and Singleton (1999) who report that both credit risk and liquidity factors are necessary to explain changes in US swap rates.

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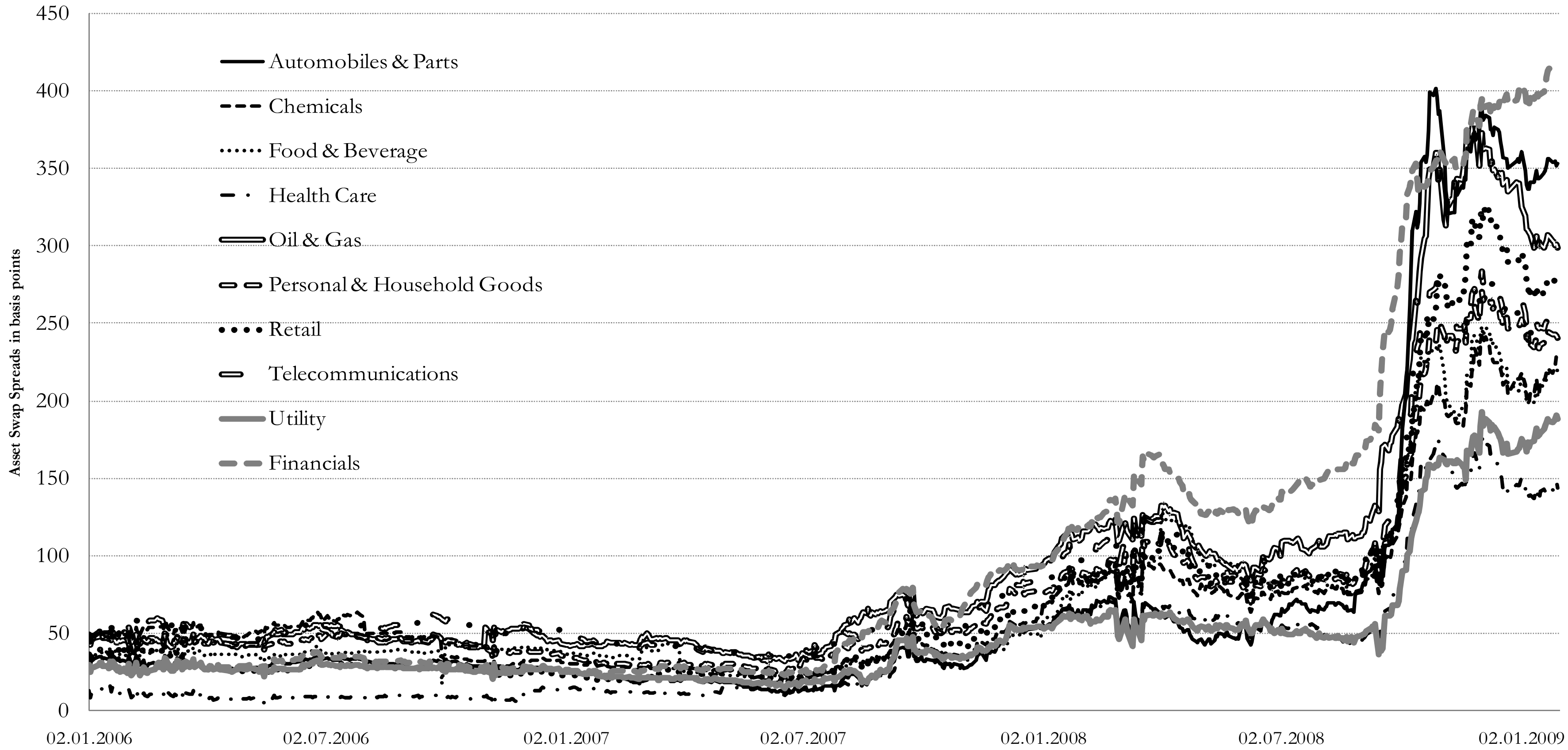
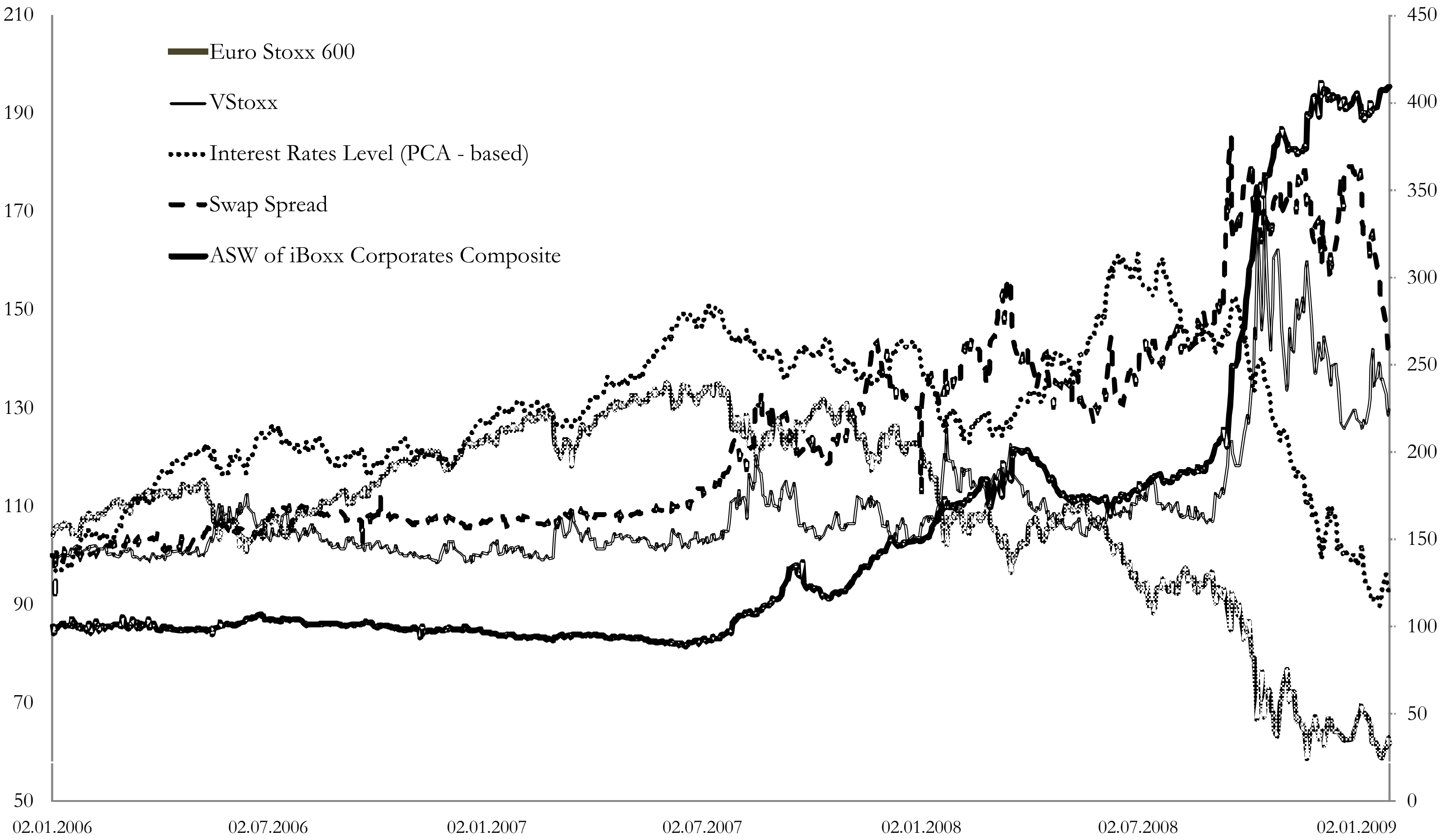
Figure 1. Sample ASW spreads stratified by industry sectors.



Note: This table presents the development of ASW spreads (in basis points) for ten selected industry sectors included in our sample, from January, 1st 2006 until January, 30th 2009.

Figure 2. The iBoxx Corporates Composite ASW spread and its determinants.



Note: Left hand scale: Determinants of Asset Swap spreads. Right hand scale: Asset Swap spread for the iBoxx Corporates Composite index. All series are normalized to start at 100.

Table 1 – Panel A. Descriptive statistics for iBoxx Corporate Bond Index ASW spreads.

Sector	No. of Bonds	Notional Billion €	Average Volume Mio €	Ann. Mod. Duration	Time to Mat.	Mean Daily Change	Median Daily Change	Std. Dev.	Ann. Std. Dev.	Skew-ness	Excess Kurtosis	Mean Spread	Median Spread	Stock Index (DJ Euro Stoxx sector index, if not otherwise specified)
Automobiles & Parts	50	48.1	962.5	2.72	3.54	0.41	0.00	4.27	67.74	2.29**	22.71**	70.02	32.42	Automobiles & Parts
Chemicals	31	24.7	795.2	3.96	4.94	0.23	0.01	3.06	48.60	1.53**	12.75**	67.35	51.05	Chemicalsicals
Food & Beverages	17	14.3	838.2	3.81	4.65	0.23	0.05	3.72	59.03	1.69**	19.93**	67.17	39.58	Food & Beverages
Health Care	17	15.3	900.0	4.56	5.83	0.17	-0.01	2.79	44.29	1.44**	12.54**	39.93	15.27	Health Care
Oil & Gas	32	27.9	872.0	3.75	5.13	0.32	0.06	3.61	57.28	0.22*	21.06**	94.08	53.67	Oil & Gas
Personal & Household Goods	28	24.8	886.1	4.15	5.36	0.25	0.03	2.98	47.32	1.81**	14.47**	74.55	48.03	Personal & Household Goods
Retail	27	21.0	777.8	3.56	4.99	0.31	0.04	3.27	51.98	1.91**	11.64**	70.46	36.50	Retail
Telecommunications	93	92.2	991.8	3.97	5.68	0.26	-0.01	3.02	47.88	1.94**	14.66**	83.88	55.81	Telecommunications
Utility	117	95.0	811.9	5.11	6.87	0.20	0.01	2.68	42.60	1.47**	17.76**	48.30	29.53	Utility
Corporates AAA	36	49.0	1360.4	4.22	5.67	0.22	0.01	3.67	58.27	3.53**	43.59**	28.81	4.79	DJ Euro Stoxx 600
Corporates AA	251	273.0	1087.5	3.74	4.91	0.29	0.06	2.91	46.27	1.57**	21.43**	55.74	12.55	DJ Euro Stoxx 600
Corporates A	552	471.3	853.9	3.94	5.41	0.46	0.09	2.88	45.78	1.72**	12.37**	98.71	40.53	DJ Euro Stoxx 600
Corporates BBB	243	191.7	789.1	3.73	5.38	0.50	0.06	3.21	50.97	2.57**	16.48**	119.55	65.54	DJ Euro Stoxx 600
Corporates Senior	811	760.9	938.3	3.87	5.16	0.30	0.03	2.70	42.86	2.08**	14.81**	68.49	32.05	DJ Euro Stoxx 600
Corporates Subordinated	271	224.1	826.9	3.78	5.68	0.86	0.21	3.28	52.10	2.23**	10.35**	153.60	62.49	DJ Euro Stoxx 600
Corporates Composite	1082	985.0	910.4	3.85	5.28	0.40	0.09	2.73	43.27	2.13**	13.99**	87.79	39.52	DJ Euro Stoxx 600
Non-financials	527	449.7	853.4	4.12	5.57	0.29	0.02	2.79	44.25	1.70**	13.25**	74.64	42.93	FTSE World Europe ex Fin.
Financials	555	535.3	964.5	3.60	5.04	0.50	0.14	2.94	46.70	2.50**	16.40**	98.90	36.23	Financials
Financials Senior	284	318.5	1121.6	3.54	4.63	0.32	0.09	2.99	47.41	2.41**	20.41**	61.28	16.08	Financials
Financials Subordinated	271	216.8	799.9	3.73	5.64	0.87	0.22	3.28	52.04	2.25**	10.63**	151.13	57.98	Financials
Banks	429	423.9	988.0	3.58	4.94	0.47	0.13	3.11	49.41	3.93**	37.98**	92.10	34.15	Banks
Tier 1 Capital	83	62.2	749.4	3.47	6.31	1.77	0.36	6.36	100.90	3.87**	24.41**	243.54	98.66	Financials
Lower Tier 2 Capital	125	102.8	822.6	3.77	5.05	0.56	0.17	2.94	46.73	2.49**	16.07**	95.83	25.80	Financials

Note: Statistics for the respective iBoxx Corporate Bond Index Asset Swap (ASW) Spreads from January 1st, 2006 until January 30th, 2009 (779 daily observations for each sector). The number of constituents in the respective iBoxx index is given in the first column. Annualized Modified Duration and Time to Maturity (Mat.) are given in years. The mean and median daily change of ASW spreads is given in basis points. The standard deviation of daily changes is given in basis points and the annualized Standard Deviation is given in annualized basis points. The mean and median of ASW spreads are denoted in basis points. Finally the respective stock index for every ASW sector is reported in the last column. These are the corresponding DJ Euro Stoxx sector indexes (depart from the group of non-financial firms where the FTSE World Europe ex Financials index is used) and the DJ Euro Stoxx 600 index (Stoxx 600). ** and * denote significance at the 1% and 5% level, respectively.

Table 1 – Panel B: Descriptive statistics for determinants of ASW spreads

Independent variables	Mean	Median	Std. Dev.	Skewness	Excess Kurtosis	Expected relation with ASW changes
Stock index returns:						
DJ Euro Stoxx 600	-0.00063	0.00044	0.01553	-0.12331	7.73886	-
Automobiles & Parts	-0.00071	0.00015	0.02094	0.08734	9.12611	-
Chemicals	-0.00020	0.00072	0.01705	-0.14978	9.82896	-
Food & Beverages	-0.00018	0.00088	0.01345	-0.55294	5.14338	-
Health Care	-0.00049	-0.00029	0.01456	0.04252	7.24707	-
Oil & Gas	-0.00049	0.00029	0.01962	0.34371	10.24587	-
Personal & Household Goods	-0.00052	0.00031	0.01570	0.24900	5.89605	-
Retail	-0.00030	0.00013	0.01516	-0.16217	5.19435	-
Telecommunications	-0.00020	0.00019	0.01437	0.28380	10.37985	-
Utility	-0.00006	0.00053	0.01728	0.58444	15.59000	-
Financial	-0.00114	-0.00021	0.02083	0.20346	7.88614	-
Banks	-0.00130	-0.00041	0.02146	0.14363	7.60419	-
FTSE World Europe ex Fin.	-0.00031	0.00035	0.01571	0.24203	9.53506	-
ΔVStoxx	0.03816	-0.05000	2.32303	1.91601	28.77801	+
ΔIR_Level	-0.00092	0.00128	0.13345	-0.17983	1.99636	-
ΔSwap Spread	0.00055	0.00100	0.02440	0.61572	24.85393	+

Note: Statistics for independent variables in equation (1) from January 1st, 2006 until January 30th, 2009 (779 daily observations for each sector). Lagged iBoxx Corporate Bond Index Asset Swap (ASW) Spreads (ΔASW_{t-1}) are not included, as their statistics are similar to the values already presented in Panel A. The stock market index returns are daily log returns ($\ln(\text{stock index}_t/\text{stock index}_{t-1})$), ΔVStoxx represents daily VStoxx index changes ($VStoxx_t$ - $VStoxx_{t-1}$), ΔIR_Level is the first principal component of a PCA using daily changes of 10 Euro swap interest rates for maturities of 1 to 10 years as input, and ΔSwap spread exhibits daily changes in the difference of the five year European swap interest rate and the yield of German government bonds of the same maturity (Swap spread_t – Swap spread_{t-1}).

Table 2. Results of Markov switching regressions.

	const.	ΔASW_{t-1}	Stock return	ΔVStoxx	ΔIR_Level	ΔSwap Spread	Std. Dev.	p_{ii}	State Duration
Automobiles & Parts									
Turbulent	0.0087**	0.3532**	-1.2998	0.4315**	-5.9386**	32.6251**	110.8669	0.8705	7.72
	(3.04)	(6.65)	(-0.44)	(8.60)	(-3.36)	(3.53)			
Calm	0.0001	-0.0945**	-11.629**	-0.0913	-2.1758**	1.1762	16.2370	0.9551	22.26
	(0.10)	(-4.49)	(-2.65)	(-1.76)	(-4.17)	(0.54)			
Chemicals									
Turbulent	0.0071	-0.0790	8.0676	0.2692	-4.9517	16.6294	85.2649	0.9237	13.11
	(1.06)	(-0.58)	(0.15)	(1.62)	(-0.52)	(0.43)			
Calm	0.0008	-0.1514	-13.7743	-0.0012	-1.7942**	0.9236	17.4629	0.9728	36.74
	(0.20)	(-0.71)	(-0.67)	(-0.02)	(-3.61)	(0.06)			
Food & Beverages									
Turbulent	0.0054	0.0025	-20.944**	0.3224**	-3.7208**	21.7357*	102.9351	0.8822	8.49
	(1.08)	(0.07)	(-3.64)	(6.00)	(-4.15)	(2.78)			
Calm	0.0007*	-0.1369*	-23.228**	-0.1020**	-1.2169*	-2.9104	14.9158	0.9556	22.54
	(2.02)	(-2.07)	(-6.55)	(-3.26)	(-2.21)	(-0.38)			
Health Care									
Turbulent	0.0055**	-0.0890	6.7733	0.2910**	-3.7628**	15.9705	75.1542	0.8744	7.96
	(3.34)	(-1.37)	(0.30)	(4.21)	(-3.47)	(1.17)			
Calm	0.0001	-0.1787*	-10.8026	-0.0061	-0.6915	1.3854	13.7207	0.9505	20.21
	(1.20)	(-2.21)	(-0.46)	(-0.04)	(-1.63)	(0.32)			
Oil & Gas									
Turbulent	0.0108	0.0344	-20.385**	0.2052**	-6.1498**	41.2796**	112.5837	0.9197	12.45
	(1.55)	(0.94)	(-3.32)	(4.30)	(-2.83)	(4.25)			
Calm	0.0012	-0.1990*	-15.0015	-0.0278	-2.8551*	0.7606	22.6032	0.9827	57.92
	(1.98)	(-2.44)	(-1.17)	(-0.41)	(-2.26)	(0.38)			
Personal & Household Goods									
Turbulent	0.0089*	-0.0870	23.8413	0.2644*	-4.8654*	17.2511	78.8854	0.8963	9.64
	(2.38)	(-1.39)	(1.05)	(2.48)	(-2.40)	(1.50)			
Calm	-0.0001	-0.0677*	-9.8711*	-0.0226	-1.1003**	3.2185	14.3114	0.9563	22.87
	(-0.35)	(-2.02)	(-2.10)	(-0.51)	(-2.68)	(1.02)			
Retail									
Turbulent	0.0094*	0.0077	20.2265	0.2877*	-3.5028	22.7682	90.9326	0.8829	8.54
	(2.01)	(0.11)	(0.93)	(2.35)	(-1.71)	(1.82)			
Calm	0.0005	-0.0733*	-12.393**	-0.0016	-1.8851**	0.5360	15.6158	0.9561	22.77
	(1.16)	(-2.28)	(-3.14)	(-0.04)	(-4.70)	(0.18)			
Telecommunications									
Turbulent	0.0063	0.0731	-2.5538	0.2558	-3.9102	18.9734	81.7654	0.9167	12.01
	(1.51)	(1.05)	(-0.10)	(1.88)	(-1.83)	(1.46)			
Calm	0.0005	-0.0150	-2.4146	0.0375	-1.4312**	3.2672	16.7733	0.9687	31.99
	(0.95)	(-0.41)	(-0.51)	(0.91)	(-3.25)	(1.03)			
Utility									
Turbulent	0.0078	-0.1778**	-22.661**	0.0412	-4.9167*	0.1832	75.7516	0.9146	11.70
	(1.30)	(-2.86)	(-5.52)	(1.30)	(-2.43)	(0.04)			
Calm	0.0004*	-0.1468**	-17.067**	-0.0436	-1.0210	-0.3179	15.6115	0.9719	35.53
	(2.45)	(-5.70)	(-2.84)	(-0.75)	(-0.97)	(-0.45)			
Corporates AAA									
Turbulent	0.0056	0.2873**	3.6822	0.2858	-3.2080	52.8956**	115.4664	0.9217	12.77
	(1.30)	(13.4)	(0.03)	(0.65)	(-0.85)	(3.27)			
Calm	0.0008**	-0.2699**	-17.7525*	-0.1043*	-1.5183**	-2.8673	16.8719	0.9827	57.82
	(2.86)	(-3.23)	(-2.17)	(-2.43)	(-2.93)	(-0.81)			
Corporates AA									
Turbulent	0.0067**	0.0579	-12.4094	0.1690**	-4.7488**	36.1258**	71.1397	0.8873	8.88
	(4.27)	(1.16)	(-1.15)	(4.60)	(-5.72)	(3.49)			
Calm	0.0005*	-0.1470	-14.7228	-0.0247	-1.6224**	-0.9396	12.3050	0.9454	18.31
	(2.06)	(-0.70)	(-0.85)	(-0.33)	(-9.36)	(-0.26)			
Corporates A									
Turbulent	0.0106**	0.0798	-30.1514*	0.0993	-3.8684*	32.1492**	73.1683	0.9057	10.60
	(3.60)	(1.79)	(-2.53)	(1.71)	(-2.45)	(5.98)			
Calm	0.0013**	-0.0497	-38.5933**	-0.2036*	-1.5196**	2.5043	14.7798	0.9625	26.66
	(3.12)	(-0.17)	(-4.37)	(-2.62)	(-4.44)	(0.71)			

(*Continued*)

Table 2. Continued.

	const.	ΔASW_{t-1}	Stock return	ΔVStoxx	ΔIR_Level	ΔSwap Spread	Std. Dev.	p_{ii}	State Duration
Corporates BBB									
Turbulent	0.0129*	0.1064	-30.6951	0.1754	-3.0372	27.2616*	85.3892	0.9008	10.08
	(2.69)	(1.75)	(-1.22)	(1.26)	(-1.40)	(2.31)			
Calm	0.0011*	0.0372	-37.6421**	-0.2341**	-1.8140**	5.6972	16.2048	0.9641	27.88
	(2.21)	(1.02)	(-4.52)	(-3.98)	(-3.82)	(1.95)			
Corporates Senior									
Turbulent	0.0072*	0.0533	-22.9137	0.1612	-3.5763	29.7785**	68.5249	0.9156	11.85
	(2.19)	(0.82)	(-1.04)	(1.11)	(-1.96)	(3.65)			
Calm	0.0006	-0.1486**	-21.3212**	-0.1119*	-1.5390**	1.9404	13.2823	0.9659	29.31
	(1.57)	(-3.85)	(-3.43)	(-2.40)	(-3.99)	(0.72)			
Corporates Subordinated									
Turbulent	0.0125**	0.2536**	-25.0488	0.0315	-3.7312*	38.9976**	65.7289	0.9514	20.58
	(4.44)	(5.81)	(-1.36)	(0.23)	(-2.40)	(7.41)			
Calm	0.0015**	-0.1271**	-57.1431**	-0.2574**	-0.9427	3.5802	13.4608	0.9593	24.58
	(3.21)	(-3.65)	(-6.29)	(-4.06)	(-1.92)	(1.16)			
Corporates Composite									
Turbulent	0.0095**	0.0632	-21.1703	0.1647	-4.0552*	32.0181**	67.7992	0.9150	11.76
	(2.95)	(1.05)	(-0.97)	(1.05)	(-2.21)	(4.24)			
Calm	0.0009*	-0.0626	-30.6173**	-0.1553**	-1.4657**	3.1737	13.9057	0.9652	28.75
	(2.29)	(-1.66)	(-4.95)	(-3.79)	(-3.88)	(1.12)			
Non-financials									
Turbulent	0.0079*	0.0430	-11.6668	0.2103	-3.7366	17.7671	73.4352	0.9167	12.01
	(2.33)	(0.54)	(-0.75)	(1.75)	(-1.89)	(1.49)			
Calm	0.0004	-0.1578**	-2.4209	-0.0345	-1.6864**	2.3315	14.2543	0.9674	30.65
	(0.80)	(-2.74)	(-0.57)	(-0.64)	(-3.78)	(0.91)			
Financials									
Turbulent	0.0085	0.2071*	4.5976	0.2377	-3.9571*	48.7543**	61.6147	0.9245	13.24
	(1.81)	(2.33)	(0.35)	(1.98)	(-2.29)	(3.14)			
Calm	0.0008	-0.1671	-21.7275*	-0.0940	-1.4653	1.7697	11.6361	0.9471	18.91
	(0.92)	(-1.49)	(-2.03)	(-0.97)	(-1.11)	(0.34)			
Financials Senior									
Turbulent	0.0071*	0.2167**	8.1620	0.3798*	-4.7083**	60.5424**	72.1853	0.8483	6.59
	(2.24)	(2.95)	(0.64)	(2.19)	(-3.00)	(4.09)			
Calm	0.0007	-0.1514	1.0613	0.0671**	-1.7790**	2.2155	12.6594	0.9395	16.54
	(1.34)	(-1.24)	(0.76)	(3.15)	(-6.43)	(0.57)			
Financials Subordinated									
Turbulent	0.0130**	0.2547**	2.8750	0.1561	-4.5369**	42.3740**	65.8223	0.9520	20.85
	(4.69)	(4.85)	(0.24)	(1.59)	(-2.91)	(4.91)			
Calm	0.0013*	-0.1265*	-39.6987**	-0.1838*	-1.0896	3.0546	13.2163	0.9599	24.92
	(2.51)	(-2.38)	(-5.11)	(-2.37)	(-1.96)	(0.86)			
Banks									
Turbulent	0.0095**	0.1238*	12.2365	0.2895*	-4.4491*	44.2449**	70.7211	0.9091	11.00
	(2.78)	(2.05)	(0.73)	(2.20)	(-2.49)	(6.25)			
Calm	0.0009*	-0.1434**	-17.7257**	-0.0974**	-1.6054**	1.2231	12.0942	0.9450	18.20
	(2.37)	(-4.10)	(-5.28)	(-2.72)	(-4.21)	(0.43)			
Tier 1 Capital									
Turbulent	0.0180	0.5154**	-65.3662**	-0.0783	0.7569	47.8202**	118.6375	0.9329	14.90
	(1.35)	(8.7)	(-2.85)	(-0.51)	(0.26)	(7.39)			
Calm	0.0014	-0.0646	-74.4322	-0.3402	-0.0774	2.1095	17.1272	0.9491	19.65
	(0.68)	(-0.96)	(-1.39)	(-0.65)	(-0.06)	(1.11)			
Lower Tier 2 Capital									
Turbulent	0.0106**	0.0555	-14.3953	0.0985**	-4.7018	22.6938**	63.8301	0.9510	20.39
	(3.21)	(0.76)	(-1.55)	(3.56)	(-1.77)	(5.71)			
Calm	0.0010**	-0.1613**	-35.8535**	-0.1566	-0.9703*	0.7634	11.6346	0.9609	25.60
	(4.22)	(-2.71)	(-2.97)	(-1.52)	(-2.63)	(0.52)			

Note: Results for the Markov switching regression of changes in European iBoxx Corporate Bond Index Asset Swap (ASW) spreads on theoretical determinants. We report regression coefficients and corresponding z-statistics (in parentheses). The results are based on a Newey-West consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity. The theoretical determinants are: lagged ASW changes (ΔASW_{t-1}), daily stock index returns (Stock return), the change in the VStoxx volatility index ΔVStoxx, the change in the level of the swap curve (ΔIR_Level), and the difference of the swap and the German government yield curve (ΔSwap Spread). The regime (turbulent and calm) dependent residual standard deviation (Std. Dev.) is in annualized basis points. p_{ii} gives the probability of staying in the respective regime. The regime dependent State Duration is in days. ** and * denote significance at the 1% and 5% level, respectively.

Table 3. Regime specific moments of ASW spreads.

		Turbulent regime			Calm regime		
	Time in turbulent regime	Mean	Skewness	Excess kurtosis	Mean	Skewness	Excess kurtosis
Automobiles & Parts	17.8%	2.27	0.59	2.31	0.01	0.08	1.29
Chemicals	26.8%	0.76	0.66	2.00	0.04	0.33	0.54
Food & Beverages	25.9%	0.75	0.73	3.54	0.06	0.02	0.55
Health Care	27.9%	0.55	0.64	1.91	0.03	0.31	0.56
Oil & Gas	16.3%	1.80	-0.42	2.95	0.04	0.06	0.97
Personal & Household Goods	27.3%	0.92	0.73	2.36	0.00	0.25	0.36
Retail	24.6%	1.12	0.73	1.00	0.05	0.25	0.83
Telecommunications	25.0%	0.95	0.82	2.22	0.03	0.21	0.34
Utility	22.6%	0.74	0.56	2.96	0.05	0.26	0.49
Corporates AAA	18.1%	0.97	1.46	6.75	0.06	0.23	1.23
Corporates AA	28.5%	0.92	0.60	4.99	0.04	0.36	0.95
Corporates A	26.8%	1.33	0.59	1.82	0.14	0.42	0.78
Corporates BBB	25.3%	1.63	1.03	2.51	0.13	0.46	0.67
Corporates Senior	28.0%	0.95	0.89	2.60	0.05	0.41	0.73
Corporates Subordinated	43.9%	1.84	1.17	3.22	0.10	0.34	0.59
Corporates Composite	27.3%	1.19	0.87	2.29	0.10	0.44	0.64
Non-financials	26.8%	0.98	0.64	2.02	0.04	0.37	0.66
Financials	39.3%	1.16	1.34	5.06	0.08	0.29	0.86
Financials Senior	25.7%	1.10	1.00	3.60	0.06	0.20	1.18
Financials Subordinated	48.1%	1.74	1.26	3.88	0.08	0.25	0.81
Banks	36.6%	1.18	2.25	13.20	0.07	0.30	0.88
Tier 1 Capital	44.9%	3.85	2.37	9.85	0.09	0.42	0.81
Lower Tier 2 Capital	39.0%	1.30	1.35	5.19	0.09	0.59	2.45

Note: This table compares the regime specific moments (mean, skewness and kurtosis) of the asset swap spread changes (ΔASW_t). The value of the mean changes is reported in basis points. The second column presents the percentage of time sample indexes spent in the turbulent regime.

Table 4. Test for equality of all coefficients in different market regimes.

	LR	*p-value*
Automobiles & Parts	51.363	0.000
Chemicals	11.842	0.037
Food & Beverages	22.754	0.000
Health Care	18.663	0.002
Oil & Gas	25.864	0.000
Personal & Household Goods	18.203	0.003
Retail	14.934	0.011
Telecommunications	14.997	0.010
Utility	11.348	0.045
Corporates AAA	53.369	0.000
Corporates AA	32.940	0.000
Corporates A1	33.420	0.000
Corporates BBB	30.852	0.000
Corporates Senior	36.033	0.000
Corporates Subordinated	82.552	0.000
Corporates Composite	39.948	0.000
Non-financials	28.125	0.000
Financials	65.799	0.000
Financials Senior	57.524	0.000
Financials Subordinated	88.267	0.000
Banks	50.427	0.000
Tier 1 Capital	110.791	0.000
Lower Tier 2 Capital	49.998	0.000

Note: Results of the Engel and Hamilton (1990) test of equality of all coefficients in model (2) in different market regimes (H_0: No switching in all variables). LR represents the likelihood ratio test statistic. Corresponding p-values are presented in the last column.

Table 5. Test of equality of coefficients for individual explanatory variables in different market regimes.

	ΔASW_{t-1}		Stock $return_{t-1}$		$\Delta VStoxx_{t-1}$		ΔIR_Level_{t-1}		$\Delta Swap\ Spread_{t-1}$	
	LR	*p-value*	LR	*p-value*	LR	p-value	LR	*p-value*	LR	*p-value*
Automobiles & Parts	30.454	0.000	0.000	0.989	17.497	0.000	3.137	0.077	1.226	0.268
Chemicals	0.307	0.580	1.929	0.165	5.388	0.020	3.185	0.074	1.906	0.167
Food & Beverages	0.776	0.378	8.396	0.004	16.898	0.000	3.978	0.046	3.895	0.048
Health Care	0.494	0.482	2.751	0.097	11.109	0.001	5.218	0.022	2.755	0.097
Oil & Gas	6.645	0.010	9.828	0.002	10.411	0.001	4.416	0.036	4.416	0.036
Personal & Household Goods	0.204	0.652	1.490	0.222	6.055	0.014	4.203	0.040	3.516	0.061
Retail	0.675	0.411	0.708	0.400	5.146	0.023	1.097	0.295	3.975	0.046
Telecommunications	0.418	0.518	5.013	0.025	8.584	0.003	3.636	0.057	3.269	0.071
Utility	0.077	0.781	2.903	0.088	3.318	0.069	5.598	0.018	0.624	0.429
Corporates AAA	30.711	0.000	7.526	0.006	11.639	0.001	0.330	0.566	8.397	0.004
Corporates AA	0.511	0.475	12.920	0.000	12.145	0.000	5.485	0.019	13.321	0.000
Corporates A1	0.243	0.622	14.477	0.000	16.050	0.000	4.683	0.030	12.991	0.000
Corporates BBB	0.754	0.385	13.772	0.000	17.782	0.000	2.531	0.112	7.555	0.006
Corporates Senior	1.874	0.171	17.135	0.000	18.722	0.000	5.098	0.024	10.295	0.001
Corporates Subordinated	34.027	0.000	10.591	0.001	13.093	0.000	8.239	0.004	13.381	0.000
Corporates Composite	0.872	0.350	17.634	0.000	20.452	0.000	6.161	0.013	13.736	0.000
Non-financials	2.027	0.155	12.857	0.000	14.679	0.000	5.017	0.025	4.007	0.045
Financials	8.526	0.004	12.016	0.001	13.687	0.000	5.468	0.019	24.598	0.000
Financials Senior	5.286	0.021	15.069	0.000	17.316	0.000	4.307	0.038	24.171	0.000
Financials Subordinated	35.945	0.000	3.803	0.051	8.872	0.003	8.318	0.004	11.633	0.001
Banks	5.426	0.020	8.280	0.004	12.920	0.000	4.983	0.026	19.644	0.000
Tier 1 Capital	82.531	0.000	11.236	0.001	9.515	0.002	1.547	0.214	8.585	0.003
Lower Tier 2 Capital	10.037	0.002	8.765	0.003	10.012	0.002	10.304	0.001	5.522	0.019

Note: The theoretical determinants are: lagged squared ASW changes (ΔASW^2_{t-1}), lagged ASW changes (ΔASW_{t-1}), lagged daily stock index returns (Stock $return_{t-1}$), lagged change in the VStoxx volatility index ($\Delta VStoxx_{t-1}$), lagged change in the level of the swap curve (ΔIR_Level_{t-1}), and lagged changes in the difference of the swap and the German government yield curve ($\Delta Swap\ Spread_{t-1}$).

Table 6. Results of the tested-down Markov switching regression.

	const.	ΔASW_{t-1}	Stock return	ΔVStoxx	ΔIR_Level	ΔSwap Spread	Std. Dev.	p_{ii}	State Duration
Automobiles & Parts									
Regime 1	0.0106	0.3488**		0.4081**	-6.2517*	33.6093**	124.66	0.9068	10.73
	(3.26)	(6.83)		(6.07)	(-2.51)	(5.68)			
Regime 2	0.0005	-0.1330*	-8.2786*		-2.5116**		19.52	0.9771	43.74
	(0.92)	(-2.24)	(-2.45)		(-5.76)				
Chemicals									
Regime 1	0.0064			0.2844**	-3.9961*		84.11	0.9161	11.92
	(2.17)			(8.04)	(-2.31)				
Regime 2	0.0005			0.1343*	-1.6611**		16.98	0.9671	30.37
	(0.76)			(2.16)	(-4.38)				
Food & Beverages									
Regime 1	0.0052		-61.1444**		-4.0263**	25.9251**	103.54	0.8847	8.67
	(1.28)		(-5.82)		(-3.10)	(4.99)			
Regime 2	0.0006	-0.1277**	-13.7668**		-0.9693*		14.93	0.9560	22.73
	(2.11)	(-3.67)	(-5.14)		(-2.30)				
Health Care									
Regime 1	0.0056	-0.1470**		0.3123**	-3.6253**		74.09	0.8807	8.38
	(2.02)	(-5.19)		(9.24)	(-3.59)				
Regime 2	0.0001	-0.1885**		0.0740**			13.55	0.9500	20.02
	(1.76)	(-2.67)		(5.17)					
Oil & Gas									
Regime 1	0.0115		-21.5173**	0.2128**	-6.1856**	39.1652**	113.57	0.9230	12.99
	(1.78)		(-3.67)	(4.95)	(-2.92)	(6.03)			
Regime 2	0.0012	-0.1882*			-3.0221**		22.92	0.9839	62.05
	(1.90)	(-2.25)			(-2.88)				
Personal & Household Goods									
Regime 1	0.0091	-0.1319**		0.2265**	-4.0582*		79.59	0.8946	9.49
	(2.45)	(-2.63)		(3.51)	(-2.20)				
Regime 2	-0.0001	-0.0747*	-8.7683*		-1.1036**		14.36	0.9560	22.72
	(-0.33)	(-2.33)	(-2.33)		(-2.79)				
Retail									
Regime 1	0.0098			0.2630**			91.75	0.8819	8.47
	(2.16)			(3.63)					
Regime 2	0.0005	-0.0734*	-12.3535**		-1.9123**		15.67	0.9562	22.82
	(1.18)	(-2.41)	(-3.88)		(-5.02)				
Telecommunications									
Regime 1	0.0072			0.3294**	-3.6620*		82.68	0.9161	11.92
	(1.80)			(3.98)	(-2.10)				
Regime 2	0.0005				-1.6613**		16.93	0.9691	32.35
	(0.99)				(-4.25)				
Utility									
Regime 1	0.0085	-0.1661**	-35.1670**				77.60	0.9176	12.14
	(0.99)	(-5.31)	(-4.33)						
Regime 2	0.0004	-0.1479**	-15.7598**				15.87	0.9733	37.51
	(0.85)	(-2.73)	(-3.12)						
Corporates AAA									
Regime 1	0.0069	0.2337**		0.4457**			120.85	0.9222	12.85
	(2.45)	(10.23)		(10.21)					
Regime 2	0.0008	-0.2613**	-16.4217*	-0.1026*	-1.4853**		16.92	0.9829	58.62
	(2.78)	(-3.54)	(-2.00)	(-2.13)	(-3.68)				
Corporates AA									
Regime 1	0.0076			0.2429*	-5.3976**	36.1874**	73.18	0.8775	8.16
	(2.42)			(2.44)	(-2.86)	(2.61)			
Regime 2	0.0005				-1.8433**		12.98	0.9462	18.58
	(0.98)				(-3.92)				
Corporates A									
Regime 1	0.0116		-46.1475**		-3.8861*	27.2963**	74.65	0.9082	10.89
	(3.40)		(-3.11)		(-2.09)	(3.10)			
Regime 2	0.0013		-40.3315**	-0.2037**	-1.4728**		15.15	0.9654	28.89
	(2.92)		(-6.09)	(-4.11)	(-3.63)				
Corporates BBB									
Regime 1	0.0162					35.3960**	90.54	0.8960	9.62
	(3.79)					(3.18)			
Regime 2	0.0011		-37.9072**	-0.2362**	-1.9257**		16.29	0.9635	27.37
	(2.07)		(-4.02)	(-3.07)	(-4.09)				

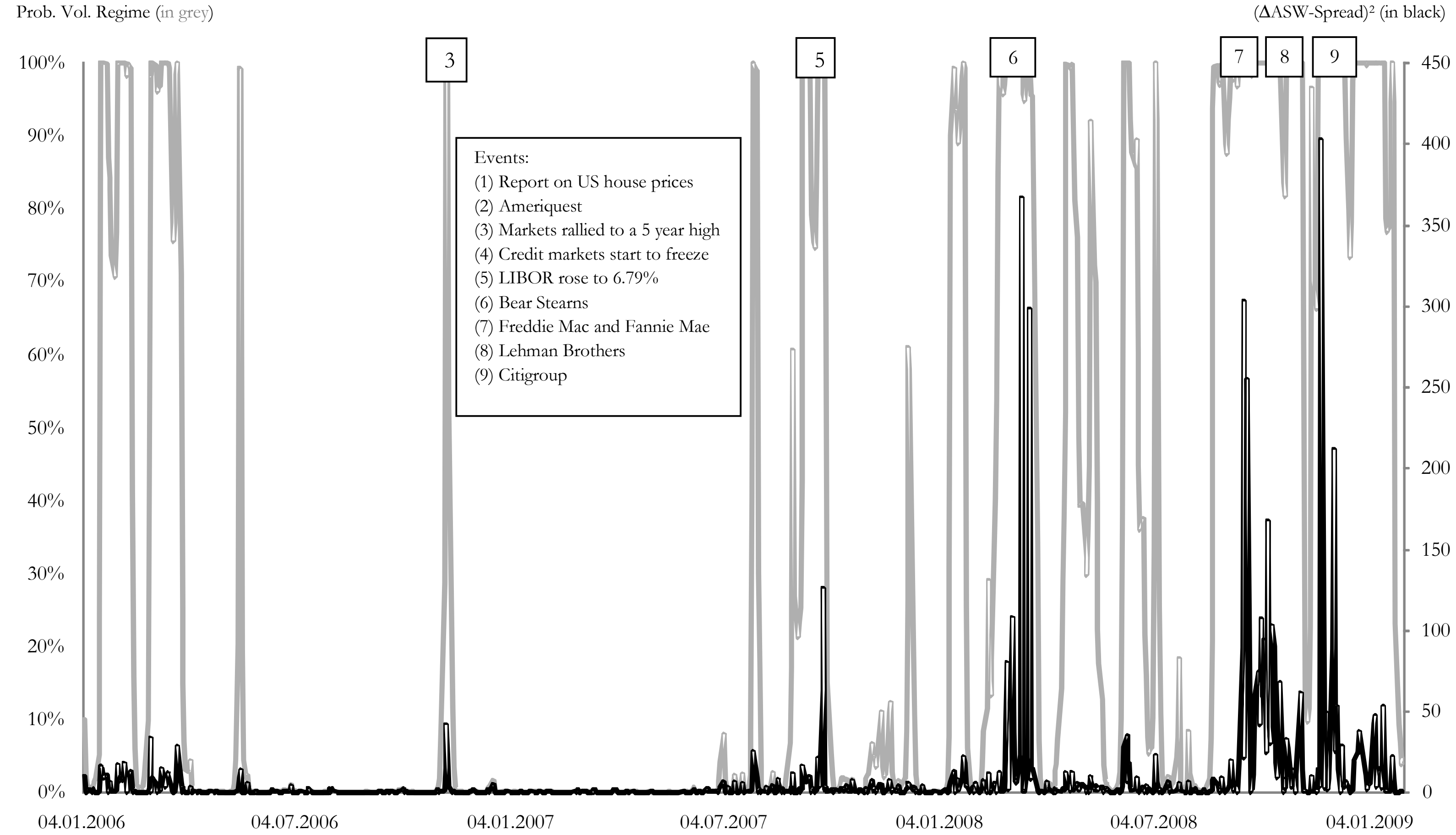
(*Continued*)

Table 6. Continued.

	const.	ΔASW_{t-1}	Stock return	ΔVStoxx	ΔIR_Level	ΔSwap Spread	Std. Dev.	p_{ii}	State Duration
Corporates Senior									
Regime 1	0.0081			0.2706**	-4.3227**	28.9963**	68.86	0.9142	11.65
	(2.53)			(3.11)	(-2.75)	(4.06)			
Regime 2	0.0006	-0.1584**	-23.4193**	-0.1246**	-1.5564**		13.32	0.9656	29.05
	(1.63)	(-4.32)	(-3.99)	(-3.07)	(-4.11)				
Corporates Subordinated									
Regime 1	0.0125	0.2665**			-5.0357**	46.8321**	66.05	0.9500	19.98
	(4.43)	(6.16)			(-4.28)	(9.71)			
Regime 2	0.0014	-0.1398**	-58.6783**	-0.2622**			13.44	0.9579	23.77
	(3.26)	(-4.04)	(-6.56)	(-4.10)					
Corporates Composite									
Regime 1	0.0095				-6.0490**	45.5067**	69.51	0.9131	11.50
	(2.86)				(-3.88)	(6.18)			
Regime 2	0.0010	-0.0873**	-33.8628**	-0.1716**	-1.4934**		14.03	0.9652	28.70
	(2.39)	(-2.41)	(-5.36)	(-3.91)	(-4.23)				
Non-financials									
Regime 1	0.0086			0.2784**	-4.3234*		73.59	0.9154	11.82
	(2.44)			(3.03)	(-2.29)				
Regime 2	0.0003	-0.1705**			-1.7253**		14.26	0.9669	30.21
	(0.68)	(-3.46)			(-3.75)				
Financials									
Regime 1	0.0084	0.2059*		0.2141**	-3.8181*	47.8193**	61.54	0.9257	13.45
	(3.32)	(2.47)		(2.77)	(-2.33)	(3.57)			
Regime 2	0.0009	-0.1700**					11.69	0.9478	19.14
	(1.43)	(-3.23)							
Financials Senior									
Regime 1	0.0068	0.2207**		0.3154*	-4.4264**	59.4865**	72.05	0.8503	6.68
	(2.45)	(2.88)		(2.37)	(-3.68)	(4.54)			
Regime 2	0.0007				-1.7846**		12.63	0.9397	16.59
	(1.19)				(-5.33)				
Financials Subordinated									
Regime 1	0.0119	0.2815**		0.1870**		42.1414**	64.26	0.9572	23.34
	(5.53)	(5.66)		(2.62)		(5.45)			
Regime 2	0.0008	-0.1310*	-24.1943**				12.10	0.9570	23.23
	(2.19)	(-2.26)	(-7.18)						
Banks									
Regime 1	0.0091	0.1282*		0.2233*	-4.0385*	42.1141**	70.91	0.9081	10.89
	(2.71)	(2.17)		(2.19)	(-2.40)	(6.40)			
Regime 2	0.0009	-0.1488**	-16.2230**	-0.0883*	-1.6226**		12.13	0.9450	18.19
	(2.48)	(-4.34)	(-4.98)	(-2.51)	(-4.41)				
Tier 1 Capital									
Regime 1	0.0171	0.5128**	-53.3296**			47.5036**	114.92	0.9449	18.16
	(1.33)	(8.06)	(-7.89)			(7.99)			
Regime 2	0.0010		-40.1955*				15.98	0.9516	20.65
	(0.37)		(-2.20)						
Lower Tier 2 Capital									
Regime 1	0.0114			0.1637*	-5.2584**	21.3912**	64.02	0.9505	20.21
	(4.95)			(2.20)	(-3.74)	(2.81)			
Regime 2	0.0010	-0.1628**	-36.4149**	-0.1590*	-0.9657*		11.65	0.9607	25.47
	(2.73)	(-3.47)	(-4.09)	(-2.16)	(-2.27)				

Note: Results for the tested-down Markov switching regression of changes in European iBoxx Bond Index Asset Swap Spreads on theoretical determinants. We report regression coefficients and corresponding z-statistics (in parentheses). The results are based on a Newey-West consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity. The theoretical determinants are: lagged ASW changes (ΔASW_{t-1}), daily stock index returns (Stock return), the change in the VStoxx volatility index (ΔVStoxx), the change in the level of the swap curve (ΔIR_Level), and the difference of the swap and the German government yield curve (ΔSwap Spread). The regime dependent residual standard deviation (Std. Dev.) is in annualized basis points. p_{ii} gives the probability of staying in the respective regime. The regime dependent State Duration is in days. ** and * denote significance at the 1% and 5% level, respectively.

Figure 3. Estimated regime probabilities and volatility of ASW spreads for Corporates Composite Portfolio.



Note: Estimated probability of being in the volatile regime - based on the filtered probability (grey bars and left scale: a value of 100% indicates being in the turbulent regime, a value of zero being in the calm regime) and squared changes in the iBoxx Corporate Composite ASW spread (black line and right scale; bps). The events are: (1) The report indicating US house price stagnation, (2) Ameriquest, (3) Markets rallied to a 5 year high (4) Credit markets freeze, (5) LIBOR reached 6.79%, (6) Bear Stearns, (7) Freddie Mac and Fannie Mae, (8) Lehman Brothers, and (9) Citigroup.

Table 7. Logit models for drivers of regime shifts.

	ΔASW^2_{t-1}	ΔASW_{t-1}	Stock $return_{t-1}$	$\Delta VStoxx_{t-1}$	ΔIR_Level_{t-1}	ΔSwap $Spread_{t-1}$
Automobiles & Parts						
	0.0215	0.0592*	-3.7964	0.0296	-1.6002*	4.6729
	(1.3180)	(2.1888)	(-0.7337)	(0.5576)	(-2.0504)	(0.9468)
	[0.0963]	[0.0115]	[0.0019]	[0.0008]	[0.0074]	[0.0021]
Chemicals						
	0.3505**	0.0662	-12.2542	0.0264	-1.3362	0.1193
	(10.103)	(1.7370)	(-1.7548)	(0.5267)	(-1.7605)	(0.0264)
	[0.4121]	[0.0072]	[0.0072]	[0.0006]	[0.0053]	[0.0000]
Food & Beverages						
	0.1033	0.0648*	-15.3480	0.0661	-1.3118	4.8336
	(1.1110)	(2.0746)	(-1.9482)	(1.4352)	(-1.7492)	(1.0914)
	[0.2002]	[0.0100]	[0.0072]	[0.0040]	[0.0051]	[0.0023]
Health Care						
	0.4450**	0.0860*	-9.5170	0.0164	-1.0351	2.8991
	(10.178)	(2.1145)	(-1.2537)	(0.3435)	(-1.4359)	(0.6898)
	[0.4074]	[0.0099]	[0.0032]	[0.0002]	[0.0032]	[0.0008]
Oil & Gas						
	0.1564**	0.1143*	-9.0381	0.0570	-1.6222	5.3706
	(10.380)	(2.2407)	(-0.9860)	(0.8961)	(-1.5414)	(0.8895)
	[0.4072]	[0.0268]	[0.0047]	[0.0030]	[0.0068]	[0.0027]
Personal & Household Goods						
	0.5183**	0.0998**	-14.1169*	0.0381	-0.8799	1.8637
	(10.972)	(2.6050)	(-1.9619)	(0.8170)	(-1.2257)	(0.4393)
	[0.4659]	[0.0152]	[0.0079]	[0.0013]	[0.0023]	[0.0003]
Retail						
	0.4002**	0.0915**	-3.5135	0.0405	-1.0232	-0.0906
	(9.8899)	(2.6755)	(-0.4828)	(0.8210)	(-1.3132)	(-0.0194)
	[0.4777]	[0.0161]	[0.0004]	[0.0015]	[0.0031]	[0.0000]
Telecommunications						
	0.4030**	0.0793*	-13.2334	0.0412	-1.6271*	2.3138
	(9.1460)	(2.1298)	(-1.6666)	(0.8575)	(-2.1035)	(0.5159)
	[0.4471]	[0.0101]	[0.0057]	[0.0015]	[0.0078]	[0.0005]
Utility						
	0.4437**	0.0963*	-8.2295	0.0398	-0.9558	2.8419
	(11.264)	(1.9925)	(-1.0364)	(0.7856)	(-1.1490)	(0.5848)
	[0.4465]	[0.0114]	[0.0031]	[0.0014]	[0.0026]	[0.0007]
Corporates AAA						
	0.2820**	0.0580	-12.4132	0.0249	-1.9375*	2.0945
	(8.4606)	(1.6561)	(-1.2783)	(0.3708)	(-2.0579)	(0.3538)
	[0.4021]	[0.0086]	[0.0058]	[0.0005]	[0.0105]	[0.0004]
Corporates AA						
	0.4806**	0.1077**	-16.7895*	0.0724	-0.7876	0.1266
	(7.3090)	(2.5942)	(-2.4332)	(1.8124)	(-1.1660)	(0.0326)
	[0.3798]	[0.0157]	[0.0112]	[0.0048]	[0.0019]	[0.0000]
Corporates A						
	0.4426**	0.1512**	-10.4261	0.0206	-0.7296	0.6953
	(10.785)	(3.4699)	(-1.4730)	(0.4458)	(-0.9945)	(0.1627)
	[0.4540]	[0.0307]	[0.0043]	[0.0003]	[0.0016]	[0.0000]

(*Continued*)

Table 7. Continued.

	ΔASW^2_{t-1}	ΔASW_{t-1}	Stock $return_{t-1}$	$\Delta VStoxx_{t-1}$	ΔIR_Level_{t-1}	ΔSwap $Spread_{t-1}$
Corporates BBB						
	0.3865**	0.1426**	-10.2304	0.0181	-0.2489	-0.1028
	(9.1046)	(3.8020)	(-1.3968)	(0.3614)	(-0.3224)	(-0.0224)
	[0.4488]	[0.0346]	[0.0041]	[0.0003]	[0.0001]	[0.0000]
Corporates Senior						
	0.5321**	0.1186**	-14.6936*	0.0434	-0.9136	0.5897
	(10.959)	(2.8624)	(-2.0244)	(0.9708)	(-1.2660)	(0.1396)
	[0.4330]	[0.0175]	[0.0086]	[0.0017]	[0.0025]	[0.0000]
Corporates Subordinated						
	0.4466**	0.1824**	-10.8897*	0.0298	-1.0134	0.4952
	(8.9094)	(5.7129)	(-2.0384)	(0.9239)	(-1.7635)	(0.1587)
	[0.3776]	[0.0473]	[0.0049]	[0.0008]	[0.0032]	[0.0000]
Corporates Composite						
	0.4929**	0.1496**	-14.5235*	0.0551	-0.8982	0.9719
	(10.416)	(3.4645)	(-2.0490)	(1.3099)	(-1.2496)	(0.2334)
	[0.4291]	[0.0272]	[0.0084]	[0.0028]	[0.0024]	[0.0000]
Non-financials						
	0.5471**	0.1204**	-9.6836*	0.0272	-1.3270	2.5513
	(10.476)	(2.8247)	(-2.0118)	(0.5743)	(-1.7852)	(0.5834)
	[0.4717]	[0.0191]	[0.0080]	[0.0006]	[0.0052]	[0.0006]
Financials						
	0.1577	0.1302**	-8.0129	0.0381	-0.5163	0.9177
	(1.0619)	(3.4984)	(-1.7909)	(1.1008)	(-0.8573)	(0.2741)
	[0.1566]	[0.0222]	[0.0047]	[0.0013]	[0.0008]	[0.0000]
Financials Senior						
	0.1285	0.1014**	-13.4546*	0.0806	-0.2518	1.9505
	(1.3689)	(2.6230)	(-2.4337)	(1.8468)	(-0.3383)	(0.4784)
	[0.1756]	[0.0159]	[0.0124]	[0.0060]	[0.0001]	[0.0003]
Financials Subordinated						
	0.4534**	0.1913**	-5.6658	0.0104	-0.7220	0.2365
	(8.5665)	(5.7485)	(-1.4263)	(0.3127)	(-1.2659)	(0.0758)
	[0.3798]	[0.0506]	[0.0024]	[0.0001]	[0.0016]	[0.0000]
Banks						
	0.5355**	0.1333**	-10.3453*	0.0539	-0.3633	1.5944
	(8.3182)	(3.4855)	(-2.2662)	(1.5029)	(-0.5814)	(0.4554)
	[0.3873]	[0.0232]	[0.0082]	[0.0027]	[0.0004]	[0.0002]
Tier 1 Capital						
	0.1082	0.1502**	-10.2846	0.0208	-0.9716	2.5760
	(1.7119)	(5.8182)	(-1.8359)	(0.5906)	(-1.6346)	(0.7679)
	[0.2752]	[0.0787]	[0.0044]	[0.0004]	[0.0029]	[0.0007]
Lower Tier 2 Capital						
	0.6208**	0.1542*	-10.1723	0.0150	-0.4266	0.8332
	(8.1869)	(4.2409)	(-1.8620)	(0.4384)	(-0.7336)	(0.2600)
	[0.3931]	[0.0287]	[0.0043]	[0.0002]	[0.0005]	[0.0000]

Note: This Table presents the α_1 coefficients from the logit regressions (see equation 3) with t-statistics (in parentheses) and R^2 [in brackets]. We use a Huber-White consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity. The theoretical determinants are: lagged squared ASW changes (ΔASW^2_{t-1}), lagged ASW changes (ΔASW_{t-1}), lagged daily stock index returns (Stock $return_{t-1}$), lagged change in the VStoxx volatility index ($\Delta VStoxx_{t-1}$), lagged change in the level of the swap curve (ΔIR_Level_{t-1}), and lagged changes in the difference of the swap and the German government yield curve (ΔSwap $Spread_{t-1}$).

Table 8. In-sample accuracy of the Markov switching model.

	Turbulent regime					Calm regime				
	Const.	β	R^2 (%)	F-stat.	N	Const.	β	R^2 (%)	F-stat.	N
Oil & Gas										
OLS	0.920	1.357	15.71	14.75	131	-0.025	0.319	3.34	17.42	647
	(1.32)	(1.01)				(-0.42)	(8.90)**			
Markov	1.265	0.974	16.27	15.44	131	0.067	0.128	0.42	2.15	647
	(1.91)	(0.10)				(1.17)	(9.99)**			
Retail										
OLS	1.303	-0.568	1.48	0.97	194	0.131	-0.252	1.62	5.38	584
	(2.82)**	(2.72)**				(2.46)*	(11.53)**			
Markov	1.148	-0.572	2.31	1.63	194	0.055	0.042	0.02	0.07	584
	(2.60)**	(3.51)**				(1.26)	(5.93)**			
Telecommunications										
OLS	1.083	-0.547	1.88	1.27	199	0.043	-0.012	0.00	0.02	580
	(2.66)**	(3.19)**				(0.87)	(10.72)**			
Markov	0.986	-0.554	3.19	2.39	199	0.042	0.186	0.14	0.51	580
	(2.52)*	(1.54)				(0.95)	(3.14)**			
Banks										
OLS	0.794	0.443	1.15	2.61	285	0.152	-0.161	0.66	2.21	493
	(2.52)*	(2.03)*				(2.46)*	(10.73)**			
Markov	1.073	-0.261	1.73	2.66	285	0.088	0.448	3.07	12.82	493
	(3.89)**	(7.98)**				(2.34)*	(4.42)**			
Corporates Composite										
OLS	0.818	0.163	0.08	0.13	344	0.053	-0.100	0.23	0.82	435
	(2.81)**	(1.88)*				(1.05)	(9.89)**			
Markov	0.931	-0.395	3.46	4.16	344	0.018	-0.048	0.04	0.13	435
	(4.39)**	(7.21)**				(0.54)	(7.96)**			

Note: This table presents results of the regressions of the actual changes in asset swap spreads (ΔASW_t) against the predicted changes (predicted ΔASW_t). The predictions are based on our Markov model (equation 1) for the two regimes (turbulent and calm) and an equivalent OLS model (using the same explanatory variables) for the entire sample period. The turbulent and calm regimes were defined using probabilities estimated by our Markov model. Observations with the estimated probabilities above 0.5 were included in the turbulent regime. T-statistics for tests of the β equals to 1 and the constant term equals to 0, are reported in brackets. N is the number of observations in the corresponding regime. ** and * denote significance at the 1% and 5% level, respectively.

Table 9. Out of sample accuracy of the Markov switching model.

		Turbulent Regime		Calm Regime	
		actual	predicted	actual	predicted
Oil & Gas					
OLS	Mean (ΔASW_t)	0.942	0.759	0.586	0.245
	SD (ΔASW_t)	6.527	1.966	3.731	1.080
	Difference (actual-predicted)	0.183		0.341	
	t-value (Difference)	(0.28)		(1.13)	
Markov	Mean (ΔASW_t)	0.942	1.411	0.586	0.174
	SD (ΔASW_t)	6.527	2.982	3.731	1.310
	Difference (actual-predicted)	-0.469		0.412	
	t-value (Difference)	(-0.70)		(1.34)	
Retail					
OLS	Mean (ΔASW_t)	1.092	0.363	0.284	0.113
	SD (ΔASW_t)	5.815	1.911	3.411	1.308
	Difference (actual-predicted)	0.729		0.171	
	t-value (Difference)	(1.44)		(0.54)	
Markov	Mean (ΔASW_t)	1.092	0.720	0.284	-0.009
	SD (ΔASW_t)	5.815	2.469	3.411	1.244
	Difference (actual-predicted)	0.372		0.293	
	t-value (Difference)	(0.71)		(0.926)	
Telecommunications					
OLS	Mean (ΔASW_t)	1.812	0.302	-0.103	0.160
	SD (ΔASW_t)	6.253	1.928	2.450	0.851
	Difference (actual-predicted)	1.510*		-0.263	
	t-value (Difference)	(2.32)		(-1.35)	
Markov	Mean (ΔASW_t)	1.812	0.661	-0.103	0.062
	SD (ΔASW_t)	6.253	2.812	2.450	0.787
	Difference (actual-predicted)	1.151		-0.165	
	t-value (Difference)	(1.69)		(-0.85)	
Banks					
OLS	Mean (ΔASW_t)	1.308	0.368	0.485	0.446
	SD (ΔASW_t)	4.852	1.414	3.794	1.089
	Difference (actual-predicted)	0.940*		0.039	
	t-value (Difference)	(2.31)		(0.11)	
Markov	Mean (ΔASW_t)	1.308	0.690	0.485	0.261
	SD (ΔASW_t)	4.852	2.036	3.794	1.263
	Difference (actual-predicted)	0.618		0.224	
	t-value (Difference)	(1.46)		(0.62)	
Corporate Composite					
OLS	Mean (ΔASW_t)	1.733	0.438	0.044	0.254
	SD (ΔASW_t)	5.155	1.540	2.200	0.969
	Difference (actual-predicted)	1.295**		-0.210	
	t-value (Difference)	(2.71)		(-1.07)	
Markov	Mean (ΔASW_t)	1.733	1.228	0.044	0.117
	SD (ΔASW_t)	5.155	2.709	2.200	0.801
	Difference (actual-predicted)	0.505		-0.073	
	t-value (Difference)	(0.98)		(-0.38)	

Note: The table presents results of testing the null hypothesis that the mean difference between actual and predicted changes in asset swap spreads is zero. The predictions are based on our Markov model (equation 1) for the two regimes (turbulent and calm) and an equivalent OLS model (with the same explanatory variables) using a rolling window of 500 (past) daily observations. The first estimation window starts on January 6th, 2006 and ends on December 18th, 2007 (500 observation). The out-of-sample period contains 278 observations (trading days), from December 19th, 2007 until January 29th, 2009. The turbulent and calm regimes are defined using probabilities estimated by the Markov model. Observations with estimated probabilities above 0.5 are included in the turbulent regime. ** and * denote significance at the 1% and 5% level, respectively.