European Asset Swap Spreads and the Credit Crisis

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Abstract

We examine time-varying behavior and determinants of asset swap (ASW) spreads for 23 iBoxx European corporate bond indexes stratified by industry, credit rating and seniority. 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 defautable 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] More recently, however, CDS trading dropped significantly whilst issuance of corporate bonds and the liquidity of the ASW market increased to record levels.[4] The popularity of corporate bonds is associated with higher returns in bond and ASW markets, and bearish equity markets. Furthermore, compared to CDS, the ASW market attracts more diverse investors and is easier to access due to their significantly smaller contract size (IFSL, 2009a; Dotz, 2007).[5]

Recent empirical evidence suggest that the changes in liquidity play an important role in price discovery and accuracy of alternative credit risk measures. Mayordomo et al. (2011), for example, show that ASW is more accurate measure of credit risk than CDS during illiquid periods. ASW spreads are a also expected to be superior measure of default risk than corporate bond credit spreads (Mayordomo et al. 2011; De Wit, 2006; Francis et al. 2003). For example, corporate bond credit spreads are affected by different tax treatment and liquidity of corporate and treasury bonds, differences in corporate bonds' contractual agreements (e.g. embedded options) and maturities (Elton et al., 2001; Cao et al., 2010).

Whilst previous studies examine determinants of credit spreads inferred from CDS indexes (Byström, 2005; Alexander and Kaeck, 2008), single name CDS spreads (Yu, 2005; Benkert, 2004; Erricson et al., 2004; Cossin et al., 2002; Hull et al., 2004)), individual corporate bonds (Collin-Dufresne et al., 2001; Tsuji, 2005), and bond portfolios/indexes (Pedrosa and Roll, 1998; Brown, 2000), ours is the first paper to examine determinants of ASW spreads inferred from European iBoxx corporate bond indexes. Most related to our work is the study of Alexander and Kaeck (2008) who examine determinants of iTraxx Europe CDS indexes during June 2004 to June 2007. We extend their model for determinants of credit spreads by considering market liquidity. The consideration of market liquidity is motivated by recent evidence that price discovery process in credit markets tend to be affected by market illiquidity (Mayordomo et al., 2011). We also contribut to the literature by examining determinants of ASW spreads for 10 industry and 13 composite iBoxx indexes stratified by their credit rating and seniority, in different market regimes. The examination of credit spreads in different market regimes is particularly important given differences in importance of various factors (global, industry, and country specific) affecting default probabilities in different market regimes (Aretz and Pope, 2012). This examination is also important in the light of recent regulatory changes which focused on CDS markets (BIS, 2003; ECB, 2004) and payied very little attention to fast growing ASW market.

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 out of sample 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 models together with an analysis of main drivers of the regime switching. This is followed by various robustness checks performed in section five. Finally section six 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.[6] Second, structural models build on Merton (1974) and use market and company fundamentals. 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.[7] For example, the risk-free interest rate is expected to be negatively related to default risk. Higher risk-free rates increase the risk-neutral drift and 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). Another argument supporting the inverse relationship between interest rates and credit spreads refers to the business cycle. For example, in periods of economic recessions interest rates tend to be lower and corporate defaults 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.

Another key variable in the structural framework is the leverage ratio, defined as the ratio of a firm's debt to its firm value. When the ratio approaches unity a default is likely to be triggered. Hence, a lower firm value (and therefore a lower equity value) increases the probability of default. Similarly, an increase in firm value volatility increases the probability of default, and, therefore, increases the credit spread. Since the firm value and its volatility are typically not directly observable we proxy for these two variables by stock market returns and implied volatility of traded stock options. Similar proxies were used in the previous literature (Huang and Kong, 2003; Alexander and Kaeck, 2008; Aretz and Pope, 2012). Aretz and Pope (2012), for example, report that equity returns efficiently capture changes in default risk. The use of the implied volatility of traded stock options is justified by the positive association between the volatility of the firm and equity volatility. Similarly, the higher stock market returns imply higher firm values and a lower probability of default. Thus, we expect a negative association between ASW spreads and stock market returns, and a positive association between ASW spreads and the stock market volatility.

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). 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 when investors' concerns about liquidity and changes in markets' perception of risk result in 'flight to quality' (Longstaff, 2004). In such an environment government bond yields usually fall more than those of other credit securities, which further leads to an increase in the swap spread.

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, expect a positive association of ASW spreads, based on European iBoxx corporate bond indexes, and swap spreads.

3. Data and methodology

3.1 Data and sample descriptive statistics

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 (Corporates, Financials, Non-financials, Tier 1 Capital, Lower Tier 2 Capital) stratified by their 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, fixed coupon rate, and should not have embedded options. Bond index values are calculated daily based on market prices, thus they represent the most accurate and timely bond pricing available.

Descriptive statistics of our sample of ASW spreads are provided in Table 1. 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.[8] 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.[9] These three sectors exhibit the highest level of (positive) skewness and excess-kurtosis.

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 *****

3.2 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. 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.[10] 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:[11]

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

The dependent variable, $\Delta\mathrm{ASW}_{k,t}$, is the change (rather than level) in the ASW spread of industry sector k on day t.[12] $\beta_{S,k,j}$ is a matrix of j regression coefficients as used in model of the $\mathrm{k^{th}}$ sector, which are dependent on the state parameter s. $\Delta\mathrm{ASW}_{k,t-1}$ is the one period lagged ASW spread change. the inclusion of lagged spread changes ($\Delta \mathrm{ASW}_{k,t-1}$) as control variable is motivated by both previous studies and properties of our sample. [13]

Equity values ($\Delta \mathrm{Stock\ return}_{k,t}$) are proxied by respective Dow Jones (DJ) Euro Stoxx indexes which are also provided by Markit (see Table 1).[14] VStoxx index ($\Delta \mathrm{VStoxx}_{t}$) is as a proxy for the implied volatility, since it is the reference measure for the volatility in European markets. The use of implied rather than historical volatility is further justified by the results of previous empirical studies on credit spreads.[15]

The change in the level of interest rates is estimated by Principal Component Analysis (PCA) using the European swap rates with maturities between one and ten years.[16] The consideration of the dynamics of the complete swap rate term structure, instead of using arbitrarily chosen maturities, is our further contribution to the literature. 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 computed eigenvalues are in fact weights, which tell us the relative importance of the level and slope shifts. The first eigenvector corresponds to a level and the second to a slope of the swap rate curve shift. The resulting first principal component of our analysis ($\Delta \mathrm{IR\_Level}_{t}$), therefore, reveals the changes in the level of the entire swap rate curve.

The swap spread ($\Delta \mathrm{Swap\ Spread}_{t}$), 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.[17] Finally, $\varepsilon_{S,k,t}$ is a vector of disturbance terms, assumed to be normal with state-dependent variance $\sigma^2_{S,k,t}$.

4. Results

4.1 Determinants of ASW spreads in different market regimes

Results of the Markov switching regressions are provided in Table 2. 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. The estimated coefficients differ considerably between the two market regimes. The majority of all sectors exhibit a negative autocorrelation during the low volatility (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.

***** 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. 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. There is, however, evidence that volatility positively influences ASW spreads especially in the turbulent regime.[18] 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.[19] 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.

The interest rate level ($\Delta\text{IR\_Level}_t$) affects ASW spreads negatively in both regimes.[20] Table 2 also reveals larger negative coefficients for interest rate levels ($\Delta\text{IR\_Level}_t$) 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 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).[21] Finally, the influence of swap spreads ($\Delta\text{Swap Spread}_t$) is positive, with extremely large coefficients, in all regressions during turbulent periods. 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 and that the recent credit crisis affected financial more than any other industry sector.

4.3 Regime probabilities and ASW spread volatility

We further examine consistency of estimated regime probabilities and the volatility of ASW spread changes $(\Delta \text{ASW}_{k,t})^2$. We expect a positive relation between volatility and estimated probabilities of entering into a turbulent period. Furthermore, we expect that the estimated probabilities relate to dates of major events during our sample period. We therefore plot the major events together with estimated probabilities and ASW spread changes (see Figure 3). 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.[22]

***** 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.

4.4 Determinants of 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 model (1) 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 model (1), 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:[23]

$$P_t = P[y_t = 1] = \frac{1}{1+e^{-(\alpha_0+\alpha_1 x_{t-1})}}, \tag{2}$$

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 4 reveals that large changes in the volatility of credit spreads, irrespective of the direction, lead to a shift in market regimes.[24] 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 4 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.

5. Robustness checks

In this section we conduct further analysis and examine the robustness of our findings. First, we test for the equality of coefficients in our Markov model in different market regimes. Second, we test-down our Markov model by excluding all explanatory variables which were not statistically significant. Third, we conduct in and out-of-sample tests for accuracy of our model's predictions.

5.1 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 $\sigma_{S_t=2}$).[25] Thus we test the following hypothesis:

$$H_0 : \beta_{S_t=1,j} = \beta_{S_t=2,j} \text{ for all } j,\ \sigma_{S_t=1} \neq \sigma_{S_t=2} \quad (3)$$

The corresponding results are reported in Table 5.

***** Insert Table 5 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.[26] 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.[27] 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 6). 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.[28] 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 6 about here *****

5.2 Tested-down Markov model

The results for tested-down Markov models are presented in Table 7. The results further highlight industry variations. For example, Automobiles & Part and all financial indexes 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. 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).[29] Notably, interest rates are an important determinant of ASW spreads in the financial sector in both regimes. This result contradicts the findings of Alexander and Kaeck (2008) who report that interest rates have no significant effect on European financial CDS sub-indexes in either regime.[30]

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

5.3. In-sample accuracy test of the Markov switching model

We assess the contribution of our Markov model to the in-sample accuracy of estimation by comparing the results of the Markov model with the results of an OLS model that uses the same explanatory variables. 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.[31] 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. Overall, the results from Table 8 show a marginal improvement in predictive power when using the Markov switching model.

5.4. Out of sample accuracy test of the Markov switching model

The predictions for the out of sample test are based on our Markov model (equation 1) 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.[32] 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, the Markov model exhibits better out of sample accuracy compared to the equivalent OLS model for determinants of ASW spreads.

6. 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 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. Similar to previous studies (Collin-Dufresne, 2001; Alexander and Kaeck, 2008) we find that credit spread changes contain a large systematic component not related to structural models of credit spreads. We identify market liquidity factor as one of the important systematic components outside structural models, especially in turbulent periods.[33]

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 Alexander and Kaeck (2008) who identify interest rates as the only driver of the regime changes for CDS spreads.

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 sectors.

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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 basis are related to CDS counterparty risk, 'soft' credit events, and inclusion of CDT options in CDS contracts (for more see Francis et al., 2003; and Blanco et al., 2005).

[4] Notional amount outstanding in CDS market dropped from $62 trillion, at the end of 2007, to $38 trillion at the beginning of 2008 (IFSL, 2009a and ISDA, 2009). Centralised clearing and voluntary termination of contracts were important contributors to the sharp drop in the liquidity of CDS market. At the same time issuance of investment grade bonds in European market has increased almost three fold, reaching E140bn mark at the beginning of 2009 (IFSL 2009b).

[5] For example, the standard CDS notional amount is 2,000 times higher (for high-yield debt) then the standard corporate bond's face value of €1,000. Consequently, CDS market was dominated by large and highly leveraged market players (Dotz, 2007).

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

[7] 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).

[8] 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).

[9]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.

[10] 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).

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

[12] 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.

[13] 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.

[14] The only exception is the equity value proxy for non-financials where the FTSE World Europe ex Financials stock index was used, as Markit does not provide relevant index.

[15] 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.

[16] 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.

[17] Time series of swap interest rates and government bond yields are from Datastream.

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

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

[20] $\Delta\mathrm{IR} - \mathrm{Level}_t$ 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.

[21] 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.

[22] By the end of 2006, 75% of all US subprime mortgages had been securitized and sold worldwide (Demyanyk and Van Hemert, 2009).
[23] The model is adopted from Clarida et al. (2006) and Alexander and Kaeck (2008).
[24] This is consistent with Alexander and Kaeck (2008) results for iTraxx Europe CDS spreads.
[25] The likelihood ratio is asymptotically $\chi^2_{(5)}$ distributed.
[26] The Tier 1 Capital sector has the highest LR-statistic.
[27] Results are available upon request.
[28] Automobiles & Parts and Chemicals at the 10% significance level. Personal & Household Goods and Utility at the 5% significance level.
[29] For Health Care interest rates are statistically significant only in turbulent period whilst for Retail only in calm period.
[30] The different results could be related to residual interest rate and funding risk associated with ASW but not with CDS spreads.
[31] For brevity we present the results for five sectors. The results for other sectors are available upon request.
[32] The turbulent and calm regimes are defined using probabilities estimated by the Markov model.
[33] 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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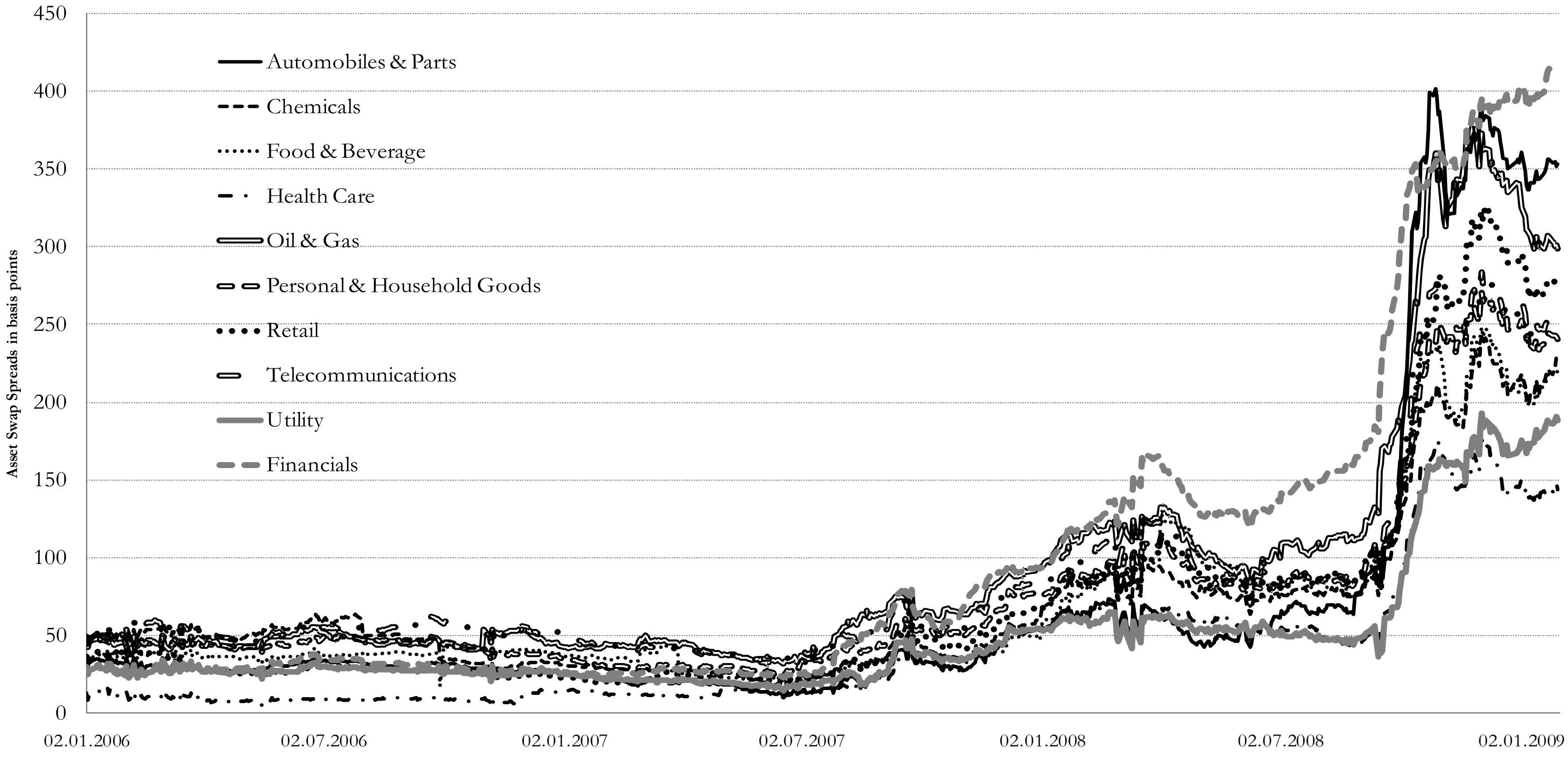
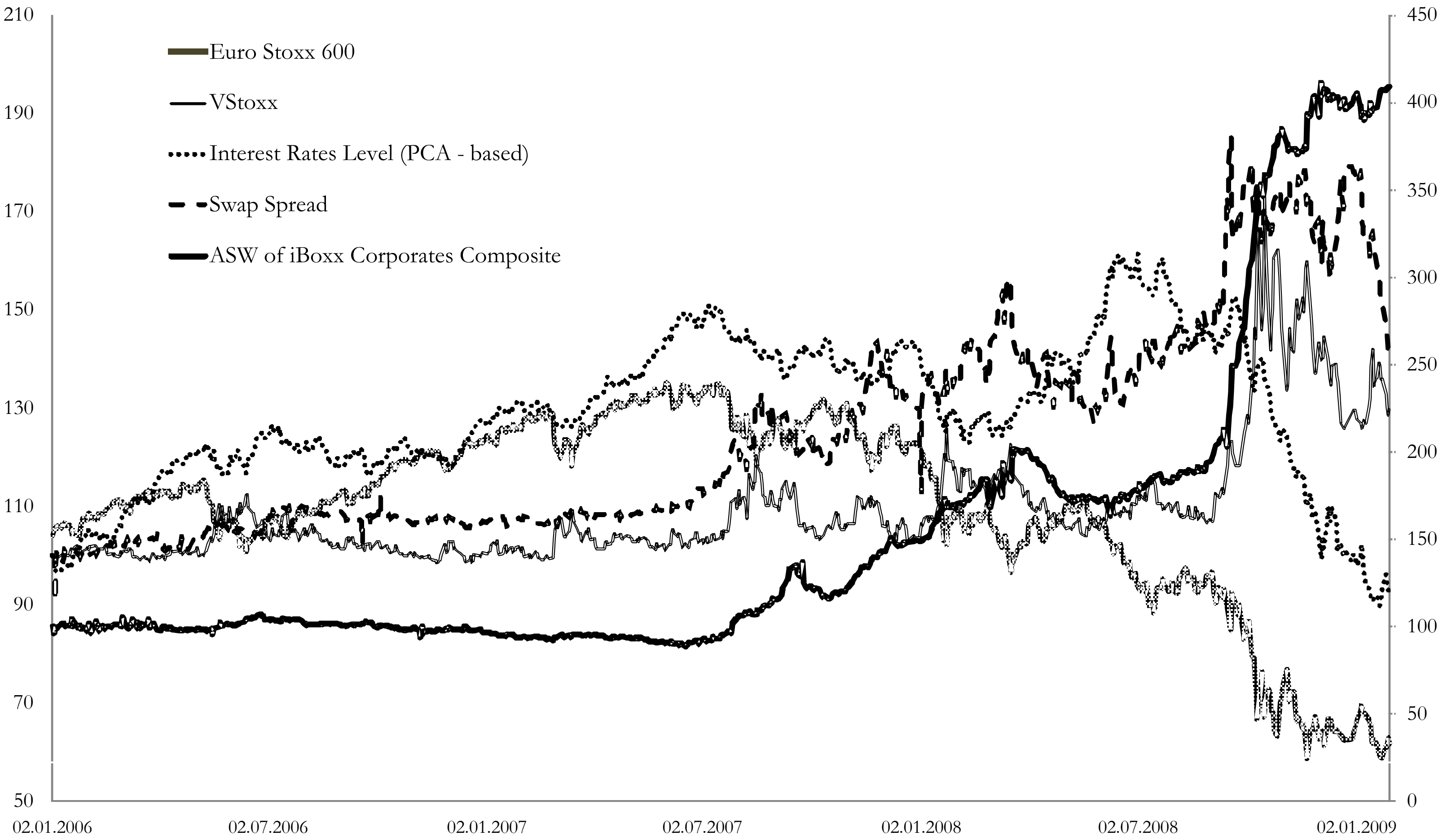
Figure 1. Sample ASW spreads stratified by industry sectors.



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. 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 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 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)			

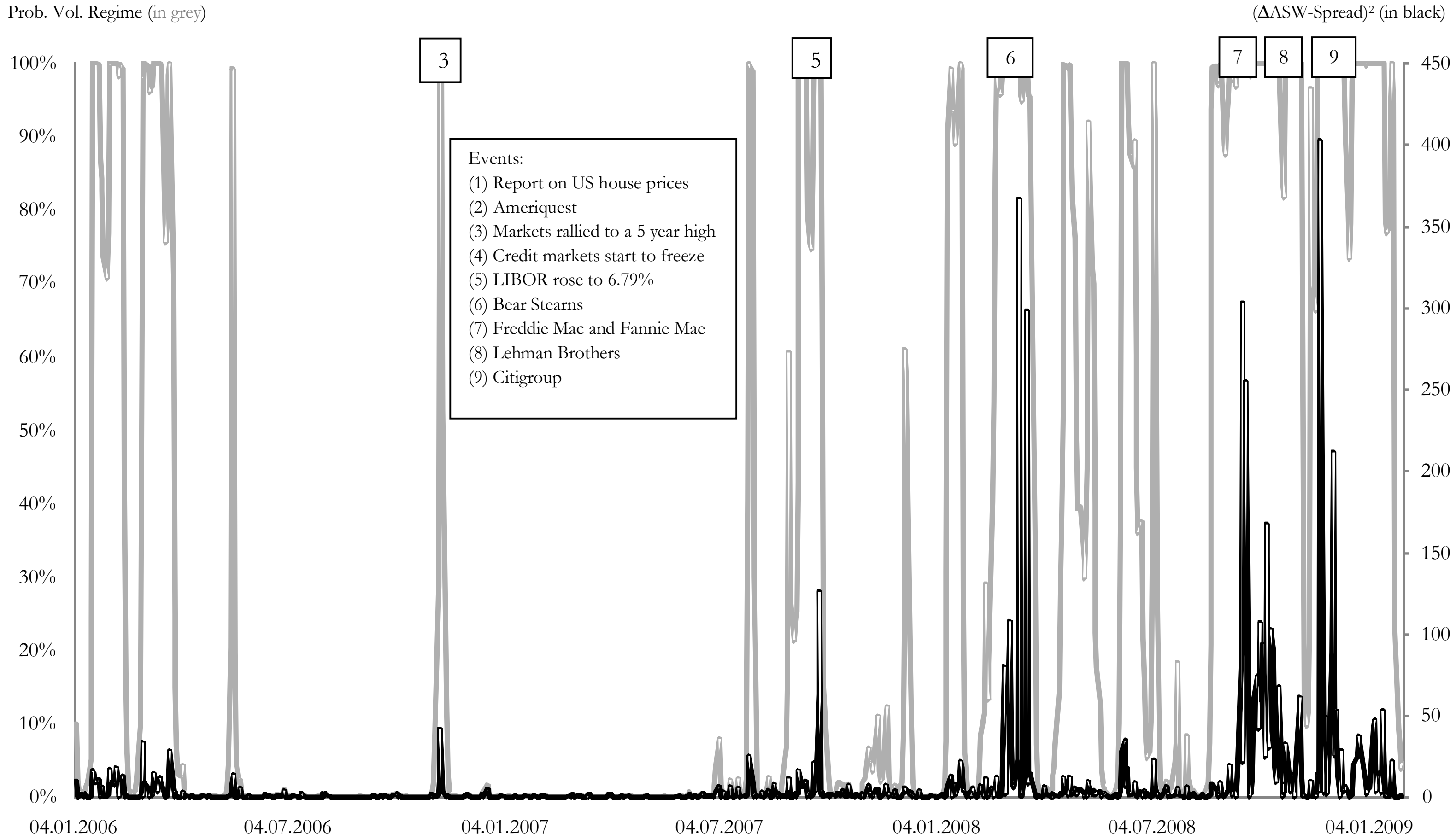
Note: Results for the Markov switching regression of changes in European iBoxx Corporate Bond Index Asset Swap (ASW) spreads on theoretical determinants. We report regression coefficients and corresponding z-statistics (in parentheses). The results are based on a Newey-West consistent estimate of the 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.

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 4. 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 4. 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 5. 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 6. 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_{t-1}^{2}), 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 7. 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	-	-13.7668**		-0.9693*		14.93	0.9560	22.73
	(2.11)	(-3.67)	(-5.14)		(-2.30)				
Health Care									
Regime 1	0.0056	-		0.3123**	-3.6253**		74.09	0.8807	8.38
	(2.02)	(-5.19)		(9.24)	(-3.59)				
Regime 2	0.0001	-		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	-		0.2265**	-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	-	-35.1670**				77.60	0.9176	12.14
	(0.99)	(-5.31)	(-4.33)						
Regime 2	0.0004	-	-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	-	-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 7. 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.

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, 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.