European Asset Swap Spreads and the Credit Crisis

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Acknowledgements:

We would like to thank Alex Kostakis, Lawrence Kryzanowski, Jun Yang, Peter Pope, Giuliano De-Rossi and participants at the 2010 Financial Management Association European Meeting (Hamburg), 2011 INQUIRE UK Autumn Seminar (Bristol), Research Seminar at University of Innsbruck (June, 2011) and University of Birmingham (October, 2011), for helpful comments and suggestions. We also thank Thomson Reuters for providing data.

Abstract

In this study we focus on asset swap (ASW) spreads as an increasingly important credit risk measure. In particular we investigate the determinants of ASW spreads for a set of 23 European corporate bond indexes during recent credit crisis. Our results suggest that ASW spreads display significant regime specific dynamics. During turbulent periods they are highly sensitive to equity market volatility whilst in calm periods they exhibit a significant association with stock returns. The level of interest rates affects ASW spreads in both regimes, whereas the difference between the swap curve and the government bond yield curve (i.e. swap spread) influences ASW spreads only in periods of increased volatility. We also find evidence of negative autocorrelation of ASW spreads in calm and positive autocorrelation in turbulent periods.

JEL classification: C13, C32, G12

***Keywords*:** European Bonds, Asset Swap Spreads, Credit Risk, Financial Crisis, Markov Switching

1. Introduction

An asset swap (ASW) is a synthetic position that combines a fixed rate bond with a fixed-to-floating interest rate swap. The bondholder effectively transforms the payoff, where she pays the fixed rate and receives the floating rate consisting of LIBOR 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. It is, therefore, a bond specific measure of credit risk implied in the bond prices and yields.

ASW are closely associated with credit derivatives such as credit default swaps (CDS).[1] For example, asset-swapped fixed-rate bonds financed in the repo market are comparable to credit default swaps (CDS) (Kakodkar et al., 2003) and are usually traded in a close range (see Norden and Weber, 2009 and Zhu, 2004).[2] Furthermore, ASW and CDS spreads tend to be cointegrated (De Wit, 2006). For the above reasons the ASW spreads represent the best cash market equivalent to CDS spreads and are regularly published by various data providers.[3] More recently, CDS trading dropped significantly to volumes that are now bellow 30% of the record levels during pre-crisis levels.[4] At the same time, the issuance of corporate bonds and the liquidity of the ASW market increased to record levels in 2009. This trend is associated with increased investors' holdings due to higher returns in bond and ASW markets and bearish equity markets. Furthermore, during the credit crisis it was much easier

[1] 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. By the end of 2008, CDS represented the largest part of the $39 trillion worth global credit derivatives market (ISDA, 2009).

[2] 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).

[3] In the strict sense ASW are not credit derivatives since they do not isolate and trade credit risk as their sole asset.

[4] Boughey (2011).

to participate in the ASW than the CDS market especially for smaller investors (IFSL, 2009a; 2009b).[5] The recorded changes in the ASW market liquidity are also consistent with evidence that ASW spreads tend to reveal information about credit risk more efficiently than CDS spreads (Gomes, 2010).[6]

Whilst previous studies examine determinants of CDS index spreads (Byström, 2005; Alexander and Kaeck, 2008), to the best of our knowledge, there are no other studies that examine determinants of ASW spreads derived from corporate bond indexes. The purpose of this study is to analyze the time-series dynamics of ASW spreads for 23 European corporate bond indexes. We contribute to the literature by examining the determinants of credit spreads before and during the recent financial crisis. We extend the model of Alexander and Kaeck (2008) by imposing a quality premium and by evaluating the time-varying behavior of credit spreads utilizing Markov switching models. The examination of the time-varying behavior of credit spreads is particularly important given the significant changes in nature of credit risk and the increasing importance of the ASW market since 2008. This examination is also important given recent regulators' interest in markets for transfer of credit risk (BIS, 2003; ECB, 2004).

Our main findings are: (i) ASW spreads behave differently during periods of financial turmoil, having a residual volatility which is up to eight times higher compared to calm periods; (ii) structural determinants explain credit spreads better for financial sector companies than for the remaining industry sectors; (iii) we find less 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 credit spreads, which is mostly negative in calm but highly positive in turbulent market periods; (v) stock market volatility determines credit spreads mainly in turbulent periods whereas stock returns are more

[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.
[6] This study examines a sample of 64 corporate bonds issued by 49 non-financial companies.

important in periods of lower volatility; (vi) interest rates are an important determinant in both market regimes; (vii) the quality premium, defined as the difference between swap and government bond yield curve tend to be relevant only in turbulent regimes; and (viii) positive returns in the stock market and increases in interest rates tend to reduce the probability of entering the volatile regime.

The remainder of this paper is organized as follows: Section two motivates our hypotheses. Section three describes data and sample characteristics. Results of OLS models for determinants of European ASW spreads and analysis of structural breaks are provided in section four. In section five 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 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 that build on Merton (1974) and use market and company fundamentals. In the structural models a default can only occur at maturity when the firm value falls below a threshold, normally associated with leverage.[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

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

[8] Several extensions of Merton's original model have been formulated. In the model of Black and Cox (1976) default can take place at any time. Leland (1994) relates debt value and capital structure to the leverage a company is assuming. Longstaff and Schwartz (1995) allow a more complex liability structure and introduce stochastic interest rates in their model. Zhou (2001) specifies the movement of the firm value as a jump-diffusion process. Hui and Lo (2002) introduce macro-economic variables and model the default threshold as a stochastic process. Aretz and Pope (2011) decompose changes in default risk and changes in determinants of default risk into global, country, and industry effects.

with market data.[9] 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, as they reflect the interbank market 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). This leads to our first hypothesis:

Hypothesis 1: ASW spreads based on European iBoxx bond indexes are negatively associated with the level of interest rates, measured by 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

[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).

volatility of a firm value increases the probability of default, and, therefore, increases the credit spread. Since 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. [10] 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 test the following hypotheses:

Hypothesis 2: ASW spreads based on European iBoxx corporate bond indexes are negatively associated with stock market returns.

Hypothesis 3: ASW spreads based on European iBoxx corporate bond indexes are positively associated with stock market volatility.

A further possible determinant of credit spreads is the difference between the swap interest rate and the interest rate of a par value government bond of the same maturity. The difference, known as the swap spread, is normally associated with liquidity and default risk (see 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 (see also Grinblatt, 2001). 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.

[10] Similar proxies were used in the previous literature. See, Huang and Kong (2003) and Alexander and Kaeck (2008).

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. This leads to our fourth hypothesis:

Hypothesis 4: ASW spreads based on European iBoxx corporate bond indexes are positively associated with swap spreads.

3. Data and sample characteristics

Our sample consists of ASW spreads for 23 different European iBoxx Corporate Bond indexes, provided by Markit. [11] 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 criteria provided by Markit.[12] 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. The indexes are rebalanced monthly. The bond index values are calculated daily based on market prices, thus they represent the most accurate and timely bond pricing available.

[11] More details on the ASW spreads for the indexes are available in Markit Group Limited (2010).

[12] Markit classifies all bonds into industry classes based on Industry Classification Benchmark (ICB).

Descriptive statistics for the sample of ASW spreads are provided in Table 1. The indexes are stratified as non-financial industrial sectors (Automobiles & Parts, Chemicals, Food & Beverage, Health Care, Oil & Gas, Personal & Household Goods, Retail, Telecommunications, and Utility), financials (Senior, Subordinated, Banks, Tier 1 Capital, and Lower Tier 2 Capital), bonds' credit rating (AAA, AA, A, and BBB), and seniority (Senior and Subordinated). 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.

The mean ASW spread for the Corporate Composite Index is 87.8 basis points. The average time to maturity of all bonds included in the Corporate Composite index is 5.28 years.[13] 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.[14] These three sectors exhibit the highest level of (positive) skewness and excess-kurtosis in our sample.

*** Insert Table 1 about here ***

[13] 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).

[14] It is worth mentioning that the Corporates AAA index only contains 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.

Figure 1 presents the co-movement of ASW spreads for ten different industry sectors. As expected, the ASW spreads for the financial sector dominate spreads for 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 and diversity of ASW spreads during the credit crisis.

*** Insert Figure 1 about here ***

4. Determinants of ASW spreads

4.1. OLS model

We start our analysis with the following linear regression model for determinants of ASW spreads:

$$\Delta\mathrm{ASW}_{k,t} = \beta_{k,0} + \beta_{k,1}\Delta\mathrm{ASW}_{k,t-1} + \beta_{k,2}\mathrm{Stock\ return}_{k,t} + \beta_{k,3}\Delta\mathrm{VStoxx}_t + \beta_{k,4}\Delta\mathrm{IR-Level}_t + \beta_{k,5}\Delta\mathrm{Swap\ Spread}_t + \varepsilon_{k,t} \quad (1)$$

where $\Delta\mathrm{ASW}_{k,t}$ is the change in the ASW spread of industry sector k on day t, $\Delta\mathrm{ASW}_{k,t-1}$ is the one period lagged ASW spread return, $\mathrm{Stock\ return}_{k,t}$ represents daily returns of the stock index for sector k, $\Delta\mathrm{VStoxx}_t$ is the change in the VStoxx volatility index, $\Delta\mathrm{IR-Level}_t$ denotes the change in the level of interest rates and $\Delta\mathrm{Swap\ Spread}_t$ represents swap spread changes.

Equity values ($\Delta\mathrm{Stock\ return}_{k,t}$) are proxied by the Dow Jones (DJ) Euro Stoxx indexes which are also provided by Markit. The equity value proxy for non-financials is the FTSE World Europe ex Financials stock index, as Markit does not offer such an index (see also Table 1). We choose the VStoxx index ($\Delta\mathrm{VStoxx}_t$) as a proxy for the implied volatility, since it is the reference measure for the volatility in European markets. The change in the level of interest rates is

estimated by Principal Component Analysis (PCA) using the European interest rate swap rates with maturities between one and ten years. [15] The resulting first principal component ($\Delta \mathrm{IR} - \mathrm{Level}_t$) reveals the changes in the level of the entire interest rate swap curve. The advantage of using PCA is that avoids subjective choice of an interest rate for a specific maturity. The final determinant included in model (1) is the swap spread ($\Delta \mathrm{Swap\ Spread}_t$), measured as the difference between the five year European swap interest rate and the yield of German government bonds of the same maturity. Time series of swap interest rates and government bond yields are from Datastream. We consider the swap spread as a quality premium, as it mainly comprises default risk and a convenience premium for holding risk-less government bonds.[16]

Byström (2006) examines determinants of CDS iTraxx index spreads and includes lagged spread changes in his model. He reports a high degree of autocorrelation in daily changes for all industry sectors. Since ASW spreads represent the cash-market equivalent to CDS spreads, a similar pattern is expected. Unreported results suggest that 15 of the 23 sample ASW spreads exhibit a highly significant degree of autocorrelation with mixed signs. Thus, the inclusion of lagged spread changes ($\Delta \mathrm{ASW}_{k,t-1}$), as a control variable, is motivated by both previous studies and properties of our sample.

The results of the regressions are presented in Table 2. They reveal signs of the coefficients that are mostly consistent with our predictions. All but one sector exhibit a negative relationship between ASW spreads and the level of interest rates ($\Delta \mathrm{IR} - \mathrm{Level}_t$). The results, therefore, support our hypothesis 1. The stock market returns negatively affect ASW spreads of most industry sectors, indicating higher spreads in bearish market conditions. The coefficients for stock market returns, however, are statistically significant only for three sectors

[15] Principal component analysis is originally developed by Spearman (1904). It is a simple and 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.
[16] See Brown et al. (2002), Kobor et al. (2005), Schlecker (2009) and Fedhutter and Lando (2008).

(Utilities, A-rated Corporate, and Corporate Subordinated). Consistent with hypothesis 3, we report a positive association between stock market volatility and ASW spreads in 21 out of the 23 regressions.[17] Overall, volatility seems to have a larger impact on ASW spreads than market returns.

*** Insert Table 2 about here ***

ASW spread changes of all sample indexes are positively associated with swap spread changes ($\Delta \text{Swap Spread}_t$). This observation is in line with our hypothesis 4. Furthermore, lagged changes of ASW spreads (ΔASW_{t-1}) are predominantly positive and statistically significant for five sample indexes. The explanatory power of the models for financial sector is higher than for non-financial sectors. [18] Tier 1 Capital sector exhibits the highest adjusted R^2 of 35%.

Cossin et al. (2002) report that changes in structural variables affect US companies with higher credit ratings less than companies with lower credit ratings. Our results in subsamples with different credit ratings are mixed. While Subordinated Corporates tend to have higher R^2 than Senior Corporates the opposite is true for AAA-rated companies compared to BBB-rated firms. Furthermore, Financials Senior and Subordinated spreads are nearly equally well explained by our model.

4.2 Evolution of ASW spreads

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 and sharply declined until

[17] In 12 regressions the positive coefficients are statistically significant, at the 5% or better. The two negative coefficients are not statistically significant.
[18] With the exception of the Automobiles & Parts sector.

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. Since then they all increased sharply with a notable jump in September 2008.

*** Insert Figure 2 about here ***

Figure 3 depicts the evolution of regression coefficients of the Stock return variable in model (1).[19] The influence of the stock market returns seems to be only slightly increasing until the summer of 2007. From mid 2007 to the very end of our sample period the stock market had a highly time-varying influence on ASW spreads with regression coefficients ranging from -3 to -96 (Corporates Senior) and -54 to -115 (Corporates Subordinated), respectively. Unreported results for all other indexes are very similar and provide further evidence for the time varying behavior of credit spreads and its determinants.

*** Insert Figure 3 about here ***

To test for potential structural breaks in the time-series of the data we employ a Chow breakpoint test (see Table 3). For the Corporates Composite, the null hypothesis of no structural break was rejected at the 1% level of significance for 81.72% of daily observations. The results for most other indexes are similar. Extreme values are observable for the Tier 1 Capital index where in 99.48% of all observations the null hypothesis of no structural breaks can be rejected at the 1% significance level. On the other hand, for Food & Beverage, Utility, and Health Care sectors the null hypothesis is rejected (at the 1% significance level) for less than 10% of observations.

*** Insert Table 3 about here ***

[19] For reasons of brevity we only show the Corporates Senior index and the Corporates Subordinated sector.

Overall, the results of our OLS model lend support to our hypotheses and are consistent with theoretical predictions. The reported time-varying properties of the parameters and the leptokurtic distribution of our sample ASW spreads, however, call for consideration of non-linearity and regime shifts.

5. ASW spreads in different market regimes

5.1 Markov switching model

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.[20] 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, therefore, estimate a two-state Markov model explaining ASW spread changes ($\Delta\mathrm{ASW}_{k,t}$), for each sector k:[21]

$$\Delta\mathrm{ASW}_{k,t} = \beta_{S,k,0} + \beta_{S,k,1}\Delta\mathrm{ASW}_{k,t-1} + \beta_{S,k,2}\mathrm{Stock\ return}_{k,t} + \beta_{S,k,3}\Delta\mathrm{VStoxx}_t + \beta_{S,k,4}\Delta\mathrm{IR-Level}_t + \beta_{S,k,5}\Delta\mathrm{Swap\ Spread}_t + \varepsilon_{S,k,t} \quad (2)$$

where $\beta_{S,k,j}$ is a matrix of j regression coefficients as used in model (1) of the $\mathrm{k^{th}}$ sector, which are dependent on the state parameter s. The explanatory variables are $\Delta\mathrm{ASW}_{k,t-1}$, which is the one period lagged ASW spread change, $\mathrm{Stock\ return}_{k,t}$ represents the daily returns of the stock index for sector k,

[20] 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) and Dionne et al. (2007).

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

ΔVStoxx_t is the change in the VStoxx volatility index, $\Delta \text{IR} - \text{Level}_t$ denotes the change in the level of the interest rate swap curve based on the first principal component, and $\Delta \text{Swap Spread}_t$ represents swap spread changes. Finally, $\varepsilon_{S,k,t}$ is a vector of disturbance terms, assumed to be normal with state-dependent variance $\sigma^2_{S,k,t}$.

Results of the Markov switching regressions are provided in Table 4. The residual volatility (Std. Dev.) is higher during the 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 positive autocorrelation in times of high volatility (turbulent regime), indicating that the data generating process consists of a mixture of different distributions. This result also explains why most of the lagged credit spread changes (ΔASW_{t-1}) have not been significant in the OLS model. 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 4 about here ***

In Non-financial sector index, stock market returns are not significantly related to ASW spread changes, 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 and Utility exhibit negative association between credit spreads and stock market returns in both regimes, as predicted by theory. In the regressions for the Financials composite index, the market returns 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.

The coefficients for VStoxx variable in both, regressions for Non-financials and Financials indexes are not statistically significant. There is, however, evidence that volatility positively influence ASW spreads especially in the turbulent regime.[22] 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.[23] The negative and statistically significant relation between volatility and credit spreads during calm periods is also observed for Corporates Composite index, in almost all credit rating (Corporates AAA, Corporates A and Corporates BBB) and seniority classes (Corporates Senior and Corporate Subordinate). The above results are counterintuitive and we believe are consequence of interactions between changes in the stock market returns and volatility implied in traded stock options. For example, all sectors with the negative relation between volatility and credit spreads also exhibit extremely high, negative and highly statistically significant coefficients for market returns during calm periods. Sharp corrections in market returns lead to a significant changes in ASW spreads and, at the same time, prices for underlying stocks. The changes in the prices for underlying stocks, in periods of modest market volatility, inevitable affect the prices for outstanding stock options (in the same direction) and consequently implied volatilities. For example, a sharp drop in market returns would lead to an increase in ASW spreads and, at the same time, to reduction in

[22] Our results are in line with Alexander and Kaeck (2008), who report similar results for changes in CDS spread indexes.
[23] It is worth noting that for the above mentioned indexes we report a positive association between volatility and credit spreads during turbulent periods.

prices for outstanding stock options (via lower prices for the underlying stocks). The lower option prices imply lower volatility. [24] The combined effect would, therefore, be a dominant negative relation between market returns and credit spreads and induced negative relation between implied volatility and ASW spreads. Overall, the results suggests that credit spreads tend to be more affected by stock market returns (i.e. levels) during calm periods while in turbulent periods stock market volatility becomes more important determinant of the credit spreads.

The interest rate level ($\Delta \mathrm{IR} - \mathrm{Level}_t$) affects ASW spreads negatively in both regimes, which is in line with hypotheses 1.[25] Table 4 also reveals larger negative coefficients for interest rate levels ($\Delta \mathrm{IR} - \mathrm{Level}_t$) 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).[26] It is worth noting that Alexander and Kaeck (2008) sample period ends before the recent credit crisis.

Finally, the influence of swap spreads ($\Delta \mathrm{Swap\ Spread}_t$) 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 strong effect on credit spreads during calm periods. For example, none of 19 coefficients for $\Delta \mathrm{Swap\ Spread}_t$ (with

[24] Some of the market corrections, for example, are associated with announcements of various policy measures contributing to a resolution of market uncertainties regarding the details and implications of the measures.

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

[26] 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).

positive sign) are statistically significant in calm periods. This evidence is in line with our hypothesis 4 suggesting that the quality 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 Financials indexes, for example, estimated duration of calm periods is 19 days compared to 13 days for turbulent periods. The respective values for Non-Financials indexes are 31 and 12 days, respectively.

5.2 Regime specific moments of ASW spread

Regime specific moments of ASW spread changes ($\Delta ASW_{k,t}$) are presented in Table 5. The first column of Table 5 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, the mean $\Delta ASW_{k,t}$ 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 Oil and Gas sector in 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, skewness 0.87 and an excess kurtosis is 2.29 (for Corporate Composite index).

Notable, the distribution of spread changes of AAA-rated Corporates and Banks is highly leptokurtic with an excess kurtosis of 6.75 and 13.2, respectively. The excess kurtosis for Retail sector is the lowest in the sample.

*** Insert Table 5 about here ***

Overall, our findings confirm that ASW spread changes deviate much more from normal distribution in the turbulent regime and that recent credit crisis affected financial more than any other industry sector.

5.3 Regime probabilities and ASW spread volatility

We further examine consistency of estimated regime probabilities and the volatility of ASW spread changes ($\Delta ASW_{k,t}$)[2]. We expect positive relation between the 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 4).

*** Insert Figure 4 about here ***

The selected events are: (1) first reports on a sharp drop in the US house price; (2) Ameriquest crisis; (3) financial markets rallied to a five year high; (4) credit markets crisis; (5) LIBOR rose to 6.79%; (6) collapse of Bear Stearns, (7) nationalisation of Freddie Mac and Fannie Mae, (8) collapse of Lehman Brothers, and (9) 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.[27]

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

Figure 4 depicts a positive association between the probabilities and ASW spread volatility and their consistency with timing of the selected events. As expected, the spikes marking increase in ASW volatility correspond to high probabilities of entering into a turbulent period (i.e. probability spikes). For example, the US housing bubble came to a sudden end when housing prices started to flatten and eventually dropped in the first quarter of 2006 (see event 1 in Figure 4). Consequently the first three months of our sample 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 4). 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 4). 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 4). 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 4). 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 4). 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 estimated probabilities, from August 2008 we basically remain in the turbulent regime until the end of our sample. Freddie Mac and Fannie Mae were nationalized at the beginning of September 2008 (see event 7 in

Figure 4). 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 4). 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 4), 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.

5.4 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 when the estimated probability from our model 2 is higher than 0.5 (indicating high volatility - turbulent regime) and equal to zero if the estimated probability value is equal to or lower than 0.5 (indicating low volatility - calm regime). The explanatory variables are the same as in our model 2, with an addition of the squared change of lagged ASW spreads (ΔASW_{t-1}^2). (ΔASW_{t-1}^2) is used as a proxy for volatility of credit spreads. The model, thus, has the following form:[28]

$$P_t = P[y_t = 1] = \frac{1}{1+e^{-(\alpha_0+\alpha_1 x_{t-1})}}, \tag{11}$$

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

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 time.

The ΔASW_{t-1}^2 column in Table 6 reveals that large changes in the volatility of credit spreads, irrespective of the direction, may lead to a shift in market regimes. The coefficients are statistically significant at the 5% or better in 18 regressions. The second column in Table 6 further exhibits that lagged changes of credit spreads (ΔASW_{t-1}) have a significant and positive influence on the regime probability (the coefficients are statistically significant at the 5% or better in 21 regressions). As expected, stock market returns have a negative sign in all sectors (statistically significant in 8 sectors), indicating that positive daily market returns reduce the probability of switching to the high volatility regime. In contrast, lagged changes in volatility ($\Delta VStoxx_{t-1}$) 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 6 about here ***

Overall, our results identify historical levels and volatility of ASW spreads as the major drivers of the regime shifts. The above results differ from Alexander and Kaeck (2008) who identified interest rates as the only driver of the regime changes.

6. 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 present results of a set of bivariate Granger-causality tests.

6.1 Equality of determinants in different market regimes

In order to evaluate the effectiveness of the Markov switching model compared to classical non-switching regressions we test if there was any switching in the parameters. Formal standard statistical tests of OLS models against a regime switching model are not valid due to unidentified parameters under the null hypothesis (Alexander and Kaeck, 2008). An alternative is proposed by Engel and Hamilton (1990). They 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 $\sigma_{S_t=2}$). Thus we test the following hypothesis:

$$H_0 : \beta_{S_t=1,j} = \beta_{S_t=2,j} \text{ for all } j,\ \sigma_{S_t=1} \neq \sigma_{S_t=2} \tag{10}$$

This specification is clearly more conservative than the hypothesis that both are switching. The likelihood ratio is asymptotically $\chi^2_{(5)}$ distributed. The corresponding results are reported in Table 7.

*** Insert Table 7 about here ***

The null hypothesis of equal coefficients in both regimes can be rejected at the 5% level, or better, for all 23 sectors. Overall, Financials provide most evidence of regimes switching. [29]

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

6.2 Granger-causality test

We further examine Granger-causality between ASW spreads and explanatory variables (Table 8). The reported p-values indicate that stock market returns and stock market volatility tend to cause changes in ASW (see first two columns in Table 8). For other structural variables the evidence is less clear and causality tend to run in both ways.

*** Insert Table 8 about here ***

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. These indexes consist of various industry sectors, different rating classes and differentiate between bonds issued by financial and non-financial firms. ASW spreads correspond to the difference between the floating part of an asset swap and the Libor or Euribor rate. While CDS spreads are subject to the functioning of the credit derivatives market, ASW spreads can be interpreted as a credit risk measure based on spot market prices. Thus, ASW spreads do not (directly) depend on the credit derivatives market.

Theoretical, as well as empirical, studies suggest four main potential determinants for credit spreads: stock market prices (as lower prices should more easily trigger default), stock market volatility (as a higher volatility increases the probability of default), the interest rate level (as in periods of economic down turn interest rates tend to be lower and corporate defaults tend to occur more often), and the spread between swap rates and government bond yields (as government bonds typically offer more liquidity, which is especially valuable in times of crisis). The above variables explain between 6% and 35% of the variations in ASW spread changes in our sample.

Our sample ASW spreads exhibit a leptokurtic distribution. For example, mean ASW spread changes are more than ten times larger in turbulent times compared to calm periods. In addition, they are also characterized by huge excess kurtosis. We also report time-varying properties of credit spread determinants. 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 observation holds in turbulent periods only 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. The above, however, 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. This result is in contrast to findings reported in studies on CDS spreads. For example, Alexander and Kaeck (2008) report that interest rates tend to be significantly (negatively) related to CDS spreads only in calm periods.

The regime transitions between turbulent and calm regimes are mainly driven by lagged values of ASW spread volatility, ASW spreads and stock returns. On the other hand, stock market volatility, interest rate levels and swap spreads are not important drivers of the 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. Finally, Granger-causality tests provide further evidence that causality runs from stock market returns and volatility to credit spreads.

Our results are important for participants in the bond markets both for valuation and hedging purposes. For example, the results suggest that ASW spreads work well as credit risk measure and provide accessible cash market alternative to CDS spreads. The interesting result is also that swap spreads tend to be a significant determinant of ASW spreads in turbulent regimes. Documented regime specific dynamics of the ASW spreads indicates that for efficient hedging of credit risk market participants should take into account differences between relevant market regimes. The regime shifts may also be important for investors in exchange traded funds (ETFs) that track our sample bond indexes. Finally, given the increasing importance of ASWs the results also provide valuable insights to regulators of the European credit risk markets.

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Table 1 Descriptive statistics for iBoxx Corporate Bond Index ASW spreads

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. The Notional for the respective bond index is given in Billion EUR. The average volume of the bond index is given in Million EUR. Annualized Modified Duration and Time to Maturity 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. ** and * denote significance at the 1% and 5% level, respectively.

Sector	No. of Bonds	Notional Billion €	Average Volume Million €	Ann.Mod. Duration	Time to Maturity	Mean Daily Change	Median Daily Change	Std. Dev.	Ann. Std. Dev.	Skewness	Excess Kurtosis	Mean Spread	Median Spread	Respective Stock Index
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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx Personal & Househo 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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx 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 Financials
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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx 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	DJ Euro Stoxx Financials

Figure 1 Sample ASW spreads stratified by industry sectors

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

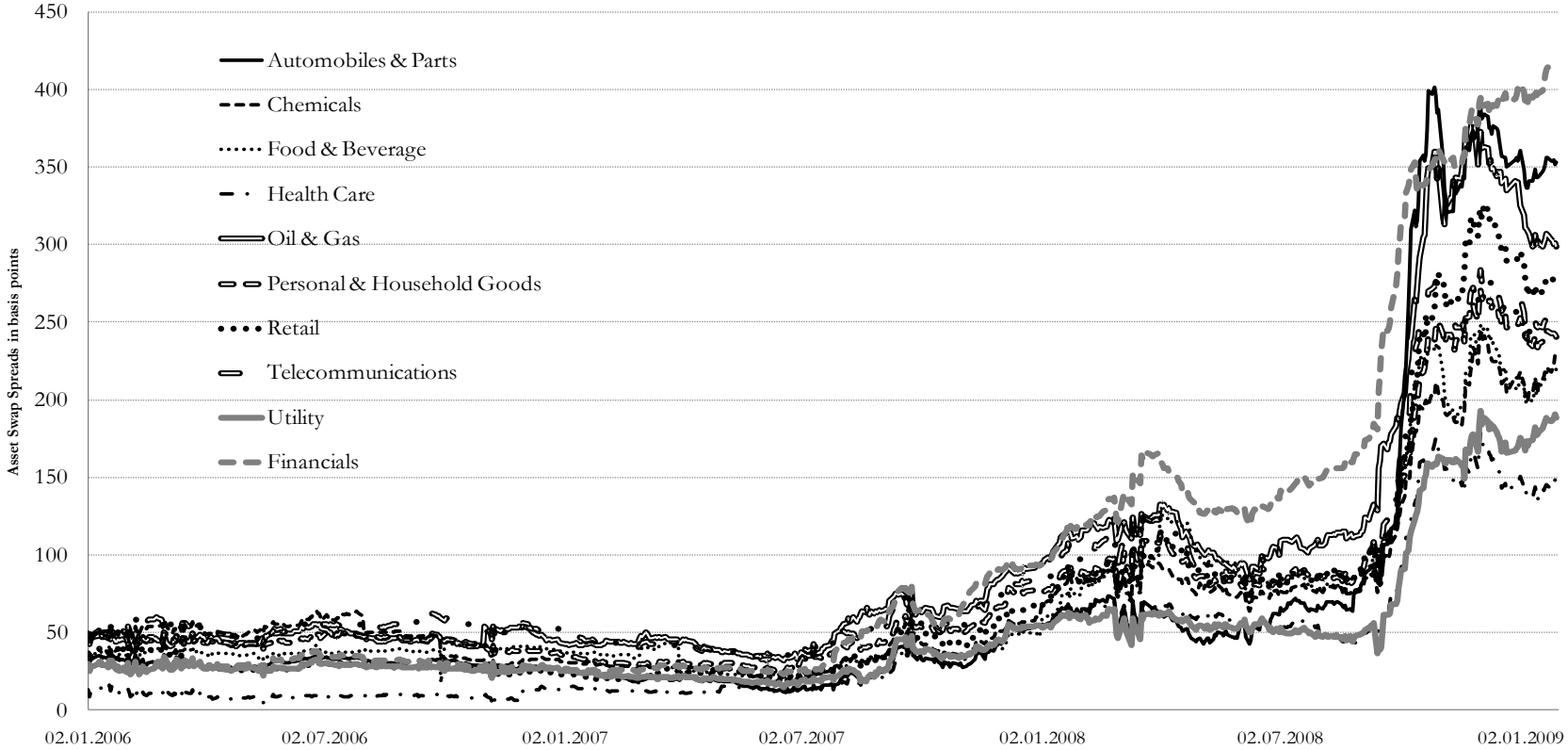

Table 2 OLS results for determinants of ASW spreads

Results of regressing daily changes in European iBoxx Corporate Bond index Asset Swap (ASW) spreads on determinants from equation 1: ΔASW_{t-1} is the lagged ASW spread change, $\Delta Stockreturn$ represents the daily returns of the respective stock index, $\Delta VStoxx$ is the change in the VStoxx volatility index, $\Delta IR-Level$ denotes the change in the level of the swap curve, and $\Delta Swap\ Spread$ is the difference of the interest rate swap and the German government bond yield curve. The sample consists of 779 daily observations from January 1st, 2006 until January 30th, 2009. We report regression coefficients, corresponding t-statistics (in parentheses) and adjusted R^2. Newey-West consistent estimates of the covariance matrix used to control for autocorrelation and heteroscedasticity. ** and * denote significance at the 1% and 5% level, respectively.

const.	ΔASW_{t-1}	Stock return	ΔVStoxx	ΔIR-Level	ΔSwap Spread	Adj. R^2
Automobiles & Parts						
0.2615	0.3068*	0.9210	0.3794**	-3.7011*	19.7132*	0.195
(1.92)	(2.26)	(0.17)	(3.60)	(-2.47)	(2.01)	
Chemicals						
0.24	-0.0926	-0.7344	0.2196*	-2.9816	8.6772	0.078
(2.03)	(-1.05)	(-0.08)	(2.02)	(-1.94)	(1.16)	
Food & Beverages						
0.2330	-0.0439	8.6440	0.3856**	-2.4384	10.7061	0.074
(1.54)	(-0.47)	(0.47)	(3.44)	(-1.68)	(1.20)	
Health Care						
0.1791	-0.1090	5.2131	0.2657**	-2.0438	9.0762	0.086
(1.74)	(-1.07)	(0.34)	(3.30)	(-1.62)	(1.27)	
Oil & Gas						
0.3016	-0.0116	-24.0346	0.1687	-2.9204	19.9049	0.110
(2.12)	(-0.13)	(-1.11)	(0.82)	(-1.88)	(1.59)	
Personal & Household Goods						
0.2575	-0.0747	9.3766	0.2160*	-2.9069*	11.2291	0.066
(2.28)	(-0.85)	(0.94)	(2.40)	(-2.53)	(1.68)	
Retail						
0.2969	0.0085	7.5184	0.2395**	-2.5535	14.1902	0.055
(2.23)	(0.10)	(0.47)	(3.22)	(-1.67)	(1.63)	
Telecommunications						
0.2284	0.0592	-1.0540	0.2379**	-2.4909	11.6075	0.073
(2.05)	(0.50)	(-0.06)	(3.42)	(-1.75)	(1.87)	
Utility						
0.2366	-0.1510	-22.2952*	0.0167	-2.7670*	0.7191	0.080
(2.44)	(-1.59)	(-2.03)	(0.17)	(-2.53)	(0.11)	
Corporates AAA						
0.1387	0.2365**	-5.3751	0.2459	-1.2295	3.1947*	0.145
(1.00)	(2.95)	(-0.18)	(1.58)	(-0.90)	(2.10)	
Corporates AA						
0.2549	0.0265	-17.7064	0.1351	-2.8248**	20.9809	0.118
(2.52)	(0.29)	(-1.21)	(1.86)	(-2.60)	(1.63)	
Corporates A						
0.3890	0.0804	-34.5794*	0.0438	-2.3197	19.7208*	0.125
(3.93)	(0.73)	(-1.98)	(0.56)	(-1.75)	(2.11)	
Corporates BBB						
0.4071	0.1280	-31.5625	0.1004	-1.9036	19.5567*	0.114
(3.80)	(1.00)	(-1.68)	(1.04)	(-1.09)	(2.56)	
Corporates Senior						
0.2652	0.0263	-22.1838	0.1375*	-2.2001	17.6829	0.129
(2.86)	(0.24)	(-1.50)	(2.03)	(-1.78)	(1.77)	
Corporates Subordinated						
0.5975	0.2628**	-37.7510*	-0.0169	-2.4047	27.9731*	0.180
(4.96)	(2.71)	(-2.02)	(-0.19)	(-1.73)	(2.42)	
Corporates Composite						
0.3439	0.0605	-2.6193	0.1048	-2.3592	1.9791	0.137
(3.68)	(0.55)	(-1.77)	(1.66)	(-1.91)	(1.94)	
Non-financials						
0.2658	0.0274	-5.0430	0.1935*	-2.5934*	12.1330	0.086
(2.59)	(0.21)	(-0.65)	(2.44)	(-2.07)	(1.58)	
Financials						
0.3831	0.1745	-5.9668	0.1908**	-2.7554*	31.9844*	0.176
(4.05)	(1.52)	(-0.63)	(2.88)	(-2.22)	(2.35)	
Financials Senior						
0.2358	0.1749	-3.9140	0.2298**	-2.3897*	34.7900*	0.180
(2.63)	(1.40)	(-0.41)	(3.00)	(-2.03)	(2.30)	

Financials Subordinated						
0.6127	0.2642**	-10.3032	0.1044	-3.0703*	29.5229*	0.172
(5.01)	(2.77)	(-0.83)	(1.31)	(-2.17)	(2.44)	
Banks						
0.3983	0.1096	-0.2551	0.2195**	-2.9245*	27.7989*	0.122
(3.60)	(1.22)	(-0.02)	(2.86)	(-2.46)	(2.30)	
Tier 1 Capital						
0.7897	0.5297**	-71.2776	-0.1031	0.9116	34.9503	0.350
(4.51)	(6.30)	(-1.85)	(-0.38)	(0.38)	(1.92)	
Lower Tier 2 Capital						
0.4981	0.0626	-24.5580	0.0546	-3.2000*	15.4047	0.094
(4.54)	(0.54)	(-1.62)	(0.68)	(-2.48)	(1.66)	

Figure 2 The iBoxx Corporates Composite ASW spread and its determinants

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.

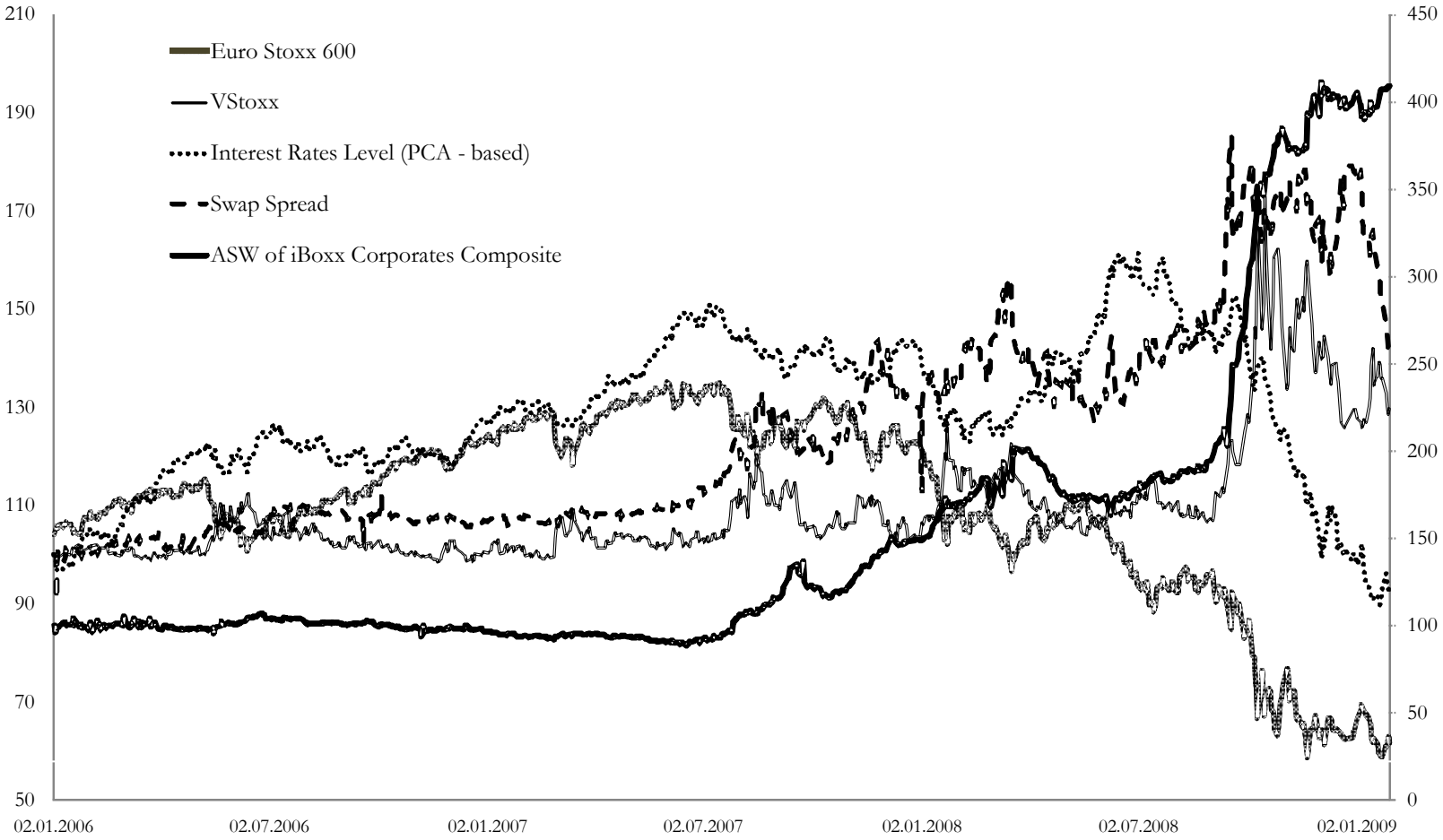

Figure 3 Evolution of OLS regression coefficients for stock market returns

This figure presents the evolution of regression coefficients of the stock market returns ($\beta_{2,k}$) in model (1). For reasons of brevity we only show the Corporates Senior and the Corporates Subordinated sector. The estimates are based on a rolling window of the last 100 observations.

Table 3 Chow breakpoint test

Rolling Chow breakpoint test for the whole sample based on model 1 (excluding the first and last 100 observations). The table provides the percentage of trading days the null hypothesis of no structural break can be rejected under the specified confidence level.

	1% Level	5% Level	10% Level
Automobiles & Parts	70.34%	89.14%	95.69%
Chemicals	10.69%	48.79%	66.03%
Food & Beverages	0.69%	16.38%	29.14%
Health Care	0.00%	9.48%	39.48%
Oil & Gas	61.21%	85.00%	96.55%
Personal & Household Goods	13.28%	52.41%	68.45%
Retail	23.62%	58.10%	73.79%
Telecommunications	11.21%	49.31%	65.52%
Utility	9.83%	31.55%	60.17%
Corporates AAA	27.24%	45.86%	68.97%
Corporates AA	42.07%	72.59%	88.62%
Corporates A	85.00%	94.66%	98.28%
Corporates BBB	80.17%	91.03%	96.03%
Corporates Senior	66.72%	87.24%	95.86%
Corporates Subordinated	96.03%	100.00%	100.00%
Corporates Composite	81.72%	93.97%	97.76%
Non-financials	52.41%	72.93%	85.17%
Financials	88.97%	97.41%	99.66%
Financials Senior	73.10%	95.52%	98.28%
Financials Subordinated	96.21%	100.00%	100.00%
Banks	78.28%	91.90%	96.03%
Tier 1 Capital	99.48%	100.00%	100.00%
Lower Tier 2 Capital	85.17%	95.86%	98.62%

Table 4 Results of Markov switching regressions

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 ($\Delta IR - Level$), 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.

	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)			
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)			

Table 5 Regime specific moments of ASW spreads

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 turbulent (volatile regime).

		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

Figure 4 Estimated regime probabilities and volatility of ASW spreads for Corporates Composite Portfolio

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 rose to 6.79%, (6) Bear Stearns, (7) Freddie Mac and Fannie Mae, (8) Lehman Brothers, and (9) Citigroup.

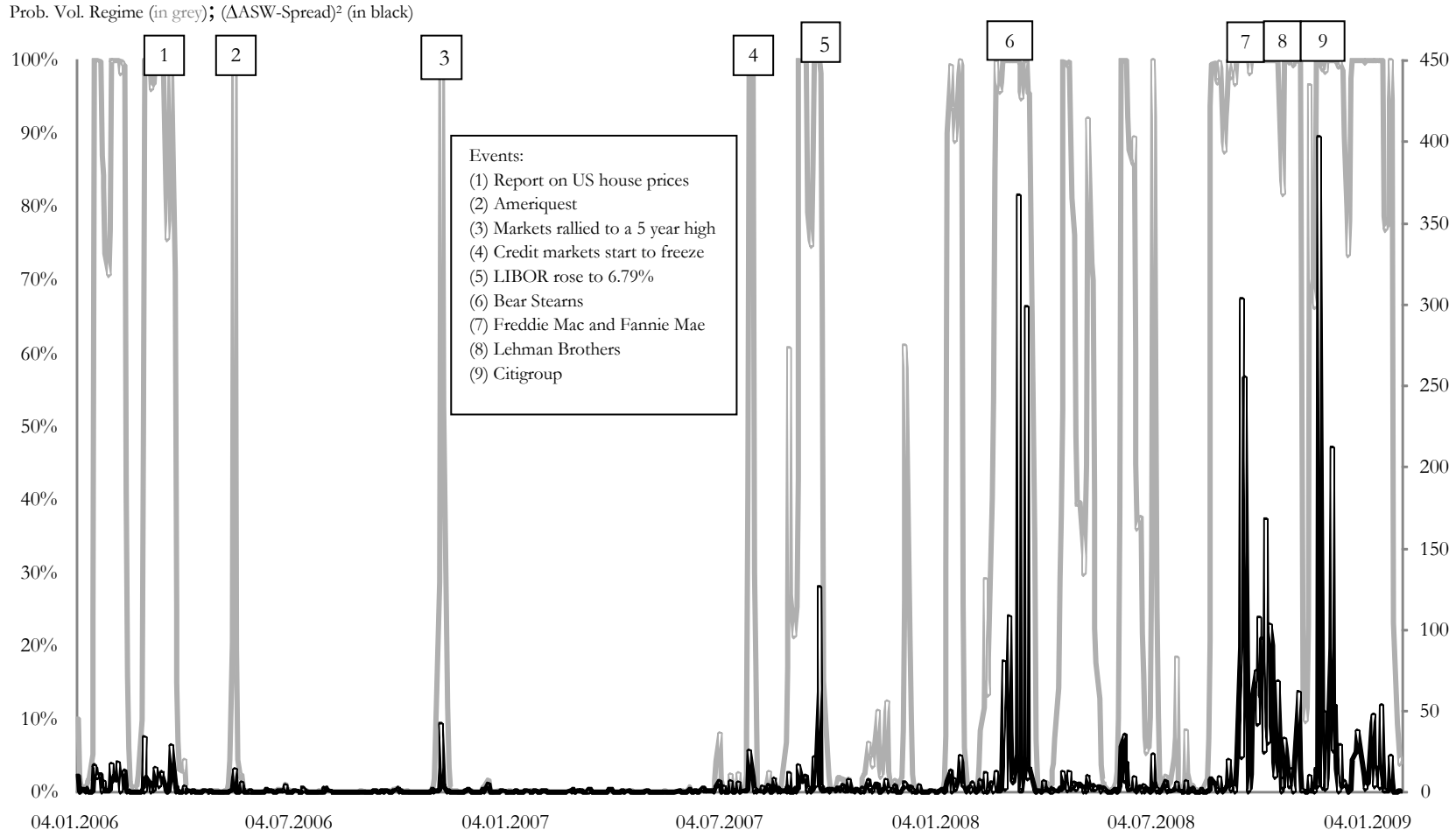

Table 6 Logit models for drivers of regime shifts

This Table presents the α_1 coefficients from the logit regressions (see equation 11) 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 ($\Delta \text{Stock return}_{t-1}$), lagged change in the VStoxx volatility index ($\Delta VStoxx_{t-1}$), lagged change in the level of the swap curve ($\Delta IR - Level_{t-1}$), and lagged changes in the difference of the swap and the German government yield curve ($\Delta \text{Swap Spread}_{t-1}$).

	ΔASW^2_{t-1}	ΔASW_{t-1}	Stock return$_{t-1}$	$\Delta VStoxx_{t-1}$	$\Delta IR\text{-}Level_{t-1}$	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]

	ΔASW^2_{t-1}	ΔASW_{t-1}	Stock return$_{t-1}$	$\Delta VStoxx_{t-1}$	$\Delta IR\text{-}Level_{t-1}$	$\Delta Swap\ Spread_{t-1}$
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]
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]

Table 7 Test for equality of determinants in different market regimes

Results of 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.

	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

Table 8 Granger-causality tests

This table presents p-values of various Granger-causality tests between dependent and our set of explanatory variables. Overall, eight hypotheses are tested: (1) Stock returns do not Granger-cause ASW spread returns, (2) ASW spread returns do not Granger-cause Stock returns, (3) ΔVStoxx do not Granger-cause ASW spread returns, (4) ASW spread returns do not Granger-cause ΔVStoxx, (5) ΔIR-Level do not Granger-cause ASW spread returns, (6) ASW spread returns do not Granger-cause ΔIR-Level, (7) ΔSwap Spread do not Granger-cause ASW spread returns, and (8) ASW spread returns do not Granger-cause ΔSwap Spread.

	Null Hypotheses:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Stock returns	ΔASW spreads	ΔVStoxx	ΔASW spreads	ΔIR-Level	ΔASW spreads	ΔSwap Spread	ΔASW spreads
	↓	↓	↓	↓	↓	↓	↓	↓
Sector	ΔASW spreads	Stock returns	ASW spreads	ΔVStoxx	ΔASW spreads	ΔIR-Level	ΔASW spreads	ΔSwap spreads
Automobiles & Parts	0.000	0.463	0.001	0.000	0.046	0.289	0.005	0.000
Chemicals	0.000	0.149	0.001	0.386	0.054	0.075	0.034	0.000
Food & Beverages	0.000	0.079	0.000	0.140	0.042	0.035	0.032	0.000
Health Care	0.001	0.000	0.000	0.454	0.159	0.144	0.009	0.000
Oil & Gas	0.018	0.000	0.005	0.000	0.006	0.000	0.053	0.000
Personal & Household Goods	0.000	0.000	0.000	0.007	0.008	0.058	0.000	0.000
Retail	0.000	0.011	0.000	0.425	0.045	0.268	0.002	0.000
Telecommunications	0.009	0.353	0.006	0.070	0.025	0.210	0.000	0.000
Utility	0.034	0.003	0.012	0.000	0.002	0.111	0.022	0.000
Corporates AAA	0.002	0.000	0.047	0.000	0.106	0.072	0.000	0.000
Corporates AA	0.001	0.366	0.063	0.366	0.064	0.108	0.000	0.000
Corporates A	0.000	0.334	0.001	0.015	0.032	0.052	0.000	0.000
Corporates BBB	0.000	0.305	0.028	0.098	0.004	0.000	0.010	0.000
Corporates Senior	0.000	0.109	0.001	0.145	0.006	0.023	0.000	0.000
Corporates Subordinated	0.000	0.014	0.001	0.012	0.039	0.000	0.000	0.000
Corporates Composite	0.000	0.415	0.013	0.163	0.016	0.035	0.000	0.000
Non-financials	0.000	0.047	0.005	0.223	0.038	0.143	0.000	0.000
Financials	0.003	0.642	0.107	0.022	0.053	0.002	0.000	0.000
Financials Senior	0.002	0.018	0.360	0.166	0.032	0.004	0.000	0.000
Financials Subordinated	0.083	0.223	0.003	0.087	0.132	0.000	0.000	0.000
Banks	0.000	0.213	0.034	0.001	0.002	0.005	0.000	0.000
Tier 1 Capital	0.018	0.000	0.001	0.000	0.615	0.000	0.048	0.179
Lower Tier 2 Capital	0.011	0.327	0.060	0.518	0.007	0.251	0.000	0.000