The Quest for Banking Stability in the Euro Area: The Role of Government Interventions

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Abstract

We build upon a Markov-Switching Bayesian Vector Autoregression (MSBVAR) model to study how the credit default swaps market in the euro area becomes an important chain in the propagation of shocks through the entire financial system. The study sheds light on the regime-dependent interconnectedness between the risk of investing in banking and public sector bonds and provides novel evidence that a rise in sovereign debt, due to the countercyclical fiscal policy measures, is perceived by stock market investors as a burden on growth prospects. We also document that government interventions in the banking sector deteriorate the credit risk of sovereign debt. Higher risk premium required by investors for holding riskier government bonds depresses the sovereign debt market, it impairs banks' balance sheets, and it depresses the collateral value of loans leading to bank retrenchment. The ensuing two-way banking-fiscal feedback loop indicates that government interventions do not necessarily stabilize the banking sector.

JEL Classification: C11, C58, G01, G21, G28.

Keywords: Banking Stability, Credit Default Swaps, Government Interventions, Markov Switching Bayesian Vector Autoregression, Sovereign Debt, Stock Market.

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1. Introduction

The global financial crisis that followed the default of Lehman Brothers in September 2008 highlighted the threat of collapse of financial institutions, alarmed the authorities, prompted large-scale state-funded rescue packages in the euro area[1], and led to an astonishing increase in banks' credit default swaps (BCDS)[2]. In the first place, those state-funded bank bailouts triggered an unprecedented deterioration in public finances of the world's major advanced economies in a peacetime period (Hryckiewicz 2014).[3] In the second place, shrinking public finances provoked fiscal imbalances in the euro area, reflected in the unprecedented increase in sovereign credit default swap (SCDS) spreads.[4]

Have tax-payer financed, colossal government rescue packages improved banking stability? Or, contrary to the conventional wisdom, have they destabilized the banking sector? What is the feedback effect – positive or negative – of bank bailouts on public finances, the risk of investment in government debt and the price of insurance against such risk? Is there evidence of regime-dependent interconnectedness between banking and public sector stability? Research into credit default swaps is dominated by the examination of i) the determinants of sovereign credit risk and defaults (Breitenfellner and Wagner 2012, Aizenman et al. 2013, Ang and Longstaff 2013 and Beirne and Fratzscher 2013), ii) the adverse effects to the banking sector during sovereign defaults (Panageas 2010, Acharya and Rajan 2013), and iii) the cost of bank bailouts to the government (Gorton and Huang 2004; Diamond and Rajan 2005). Only recently, studies on two-way feedback effects between the risk of default in the banking and public sectors have emerged (Reinhart and Rogoff 2011, Alter and Schüler 2012, Acharya et al. 2013 and Gennaioli et al. 2014). Key in this research

[1] The threat of total collapse of large financial institutions provoked large-scale rescue packages, announced by euro area governments in September 2008 in an attempt to increase the resilience of the banking sector. (Attinasi et al. 2009, Petrovic and Tutsch 2009, Veronesi and Zingales 2010, Calice et al. 2013, Phillipon and Schnabl 2013)

[2] A credit default swap (CDS) is currently the most popular credit derivative, and it serves as a key indicator for the level of credit risk (for a more detailed information on credit default swaps, see Appendix A). It can be used by investors for hedging and speculation.

[3] From 2007 to 2011, the government debt ratio as a percentage of GDP increased in all euro area countries. The increase in the debt ratio was documented to range from 9.3 percentage points (Cyprus) to 62.3 percentage points (Ireland) (Grammatikos and Vermeulen 2012).

[4] In the case of government debt, investors use CDSs to express a view about the creditworthiness of a government, and to protect themselves in the event of a country default or in the event of debt restructuring. Financial markets developed the CDS on government debt as a flexible instrument to hedge and trade sovereign credit risk. Although CDSs on government debt are only a fraction of countries' outstanding debt market, their importance has been growing rapidly since 2008, especially in advanced economies where the creditworthiness of some of these countries have experienced enormous pressure. With the intensified attention, their usage has come under more scrutiny.

is the possibility – hitherto empirically unaccounted for by the existing literature – that financial crises and government interventions in the banking sector can alter the structure of such effects thus aggravating the two-way banking-fiscal feedback loop. Uncertainty surrounding future credit ratings is identified in this study as a catalyst for the aforementioned loop. In this regard, our study conceptually resembles Kaminsky and Schmukler (2002), who ascribe financial instability to the role of government interventions.

In an attempt to fill this gap, the first and foremost objective of our research consists of examining the regime-dependent interdependence between the euro area BCDS and SCDS spreads. In particular, we focus on the two-way feedback effects between sovereign and banking sector's risks in euro area countries. We build on and extend Alexander and Kaeck (2008), who document evidence of pronounced regime-dependent behavior in the CDS market. Our research also corroborates Riedel et al. (2013), who identify regime-dependent sovereign credit risk determinants in four major Latin American economies. This methodology conveniently allows testing for the theoretical effects of sovereign defaults on the domestic private (banking and non-banking) sector derived by Sandleris (2014), and it complements the empirical effects on the domestic banking sector, documented by Correa et al. (2013).

Further, one could argue that the credit risk was simply metastasized and transferred, through bailouts (Arghyrou and Kontonikas 2012), from the banking to the public sector. However, only temporary improvement in the levels of perceived credit risk in the banking sector could be witnessed after bank bailouts. Indeed, by the first quarter of 2009, BCDS contracts were traded again at par with SCDS contracts. Since November 2009, several "peripheral" euro area countries, including Greece, Ireland, Portugal, Spain and Italy, have faced episodes of heightened turbulence in their sovereign debt markets and thus rising SCDS spreads (Bolton and Jeanne 2011). Hence, not surprisingly, the CDS market has recently received renewed attention from investors, policy makers, regulators and researchers. The ensuing sudden credit squeeze and liquidity dry-up induced stock market investors to seek protection and insurance against the increased probability of default. Thus, there are anecdotal evidences that the CDS market reflects developments in both credit and stock markets.

Against such evidence, our second objective is to achieve a better understanding of the regime-dependent relation between stock and credit markets. Further, the relation between credit and stock markets underscores the effects of stock market variables on credit market variables (see Zhang et al. 2009, Cao et al. 2010, Arouri et al. 2014, *inter alia*). While our methodology accounts for information contents of CDS and stock markets, and the stance of a business cycle, we also allow stock market returns and volatility to be endogenously determined by using BCDS and SCDS spreads. To the best of our knowledge this approach is not apparent in the literature. The direction of the interdependence between stock and credit markets has become a bone of contention only recently (Norden and Weber 2009, Hilscher et al. 2013). However, evidence on whether and, if so, how CDS spreads are informative about stock market returns and volatility, remains scant (see, e.g., Wang and Bhar 2014).

Our research significantly contributes to the literature that studies the effects of large-scale rescue packages (i.e. government interventions) provided by euro area governments to their national banking sectors on BCDS and SCDS spreads.[5] Our results are supportive of the hypothesis that government interventions in the banking sector lead to a credit risk transfer from the banking to the public sector. Additionally, the results support the two-way feedback hypothesis[6], and the hypothesis advanced by Gennaioli et al. (2014) and Sandleris (2014), which states that the expectation of support from national governments allows banks to be more leveraged, and therefore more vulnerable to sovereign defaults. Notably, our key contribution is to show that the above mentioned banking-fiscal feedback loop intensifies in a more volatile regime. Overall, we provide novel evidence that large-scale rescue packages do not necessarily stabilize the banking sector, as witnessed by rising BCDS spreads.

Second, we contribute to the literature which studies the relation between credit market and stock market variables (see, e.g. Trutwein and Schiereck 2011; Breitenfellner and Wagner 2012). The empirical results unambiguously show that an unanticipated increase in BCDS and SCDS spreads provokes a surge in investors' expectations of stock market volatility (as measured by the VSTOXX volatility index), and it leads to a decrease in the EUROSTOXX stock market index. Uniquely and innovatively, the effects of shocks to BCDS and SCDS spreads on the VSTOXX volatility index and on the EUROSTOXX stock index are larger and more significant a more volatile regime.

The rest of the paper is organized as follows. Section 2 formulates the hypotheses that are tested in this research. Section 3 outlines the methodology. Section 4 describes the characteristics of the dataset. Section 5 analyzes the estimation results. Section 6 presents the concluding remarks.

[5] Unlike Alter and Schüler (2012) who model the relation between BCDS and SCDS spreads by means of a *single-regime* VAR model, the Markov-Switching Bayesian Vector Autoregression (MSBVAR) model we use sheds light on a significant *regime-dependent* interdependence between these variables.
[6] The feedback hypothesis implies that higher risk premium required by investors for holding government bonds depresses the sovereign bond market, it impairs balance sheets of the banking sector, and it depresses the collateral value of loans.

2. The Hypotheses

In this section, we formulate the hypotheses used in our research. The hypotheses build on the relation among BCDS and SCDS spreads, the EUROSTOXX stock market index and the volatility index VSTOXX in low, intermediate and high volatility regimes of the CDS market. Our research identifies three regimes in the credit default swap market (see also section 5). These are low, intermediate and high volatility regimes. Before the subprime mortgage crisis (i.e., before July 2007), the CDS market experienced the low-volatility regime, with both BCDS and SCDS spreads showing a tendency to decrease. The intermediate volatility regime commenced in July 2007, when HSBC announced large subprime-mortgage related losses (Eichengreen et al. 2012). The high-volatility regime was triggered by the collapse of Lehman Brothers (September 2008), when financial contagion spilled over from the United States to European countries (Calice et al. 2013), and when euro are governments provided large-scale rescue packages to their national banking sectors. In the high-volatility regime, BCDS and SCDS spreads experienced an unprecedented hike that was followed again by a relatively calmer intermediate-volatility period with some tendency for the high-volatility state to recur during the sovereign debt crisis that commenced in the late 2009 in a number of peripheral euro area countries. These developments are illustrated in Panel A of Figure 1.

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2.1 The Fundamentals Channel Hypothesis

Following Gerlach et al. (2010), and Acharya et al. (2013), a systemic banking crisis causes a business-cycle recession, which weakens public finances and leads to a higher default risk of sovereign bonds. Financial institutions that suffer unanticipated outflow of deposits and experience funding and liquidity issues in the wholesale market are forced to reduce their lending activity and even to call back existing loans in order to deleverage their balance sheets. This raises the probability of default on banks' liabilities and is associated with an increase in BCDS spread. If funding and liquidity problems become a commonplace in the banking sector, money supply decreases because credit conditions deteriorate (i.e. less credit is available to finance projects in the economy). Thus, a systemic banking crisis prompts a recessionary effect on investment, consumption, income, and adverse effects on public finances. As a result, sovereign credit default risk will increase. Therefore, the first part of the Fundamentals Channel Hypothesis implies that:

Hypothesis 1.1. A positive change in banks' credit default swap spread is followed by a positive change in sovereign credit default spread, irrespective of the sovereign credit default market regime.

The hypothesis is also supported by the existence of implicit government guarantees to the banking sector. Also, we formulate a second part of this hypothesis.

Hypothesis 1.2. In a more volatile credit default swap market regime, changes in the credit risk of banks have a stronger effect on the sovereign credit risk than in a less volatile regime.

Following a systemic banking crisis, uncertainty about future economic prospects grows rapidly, driving lower the sovereign creditworthiness (i.e. SCDS spread increases reflecting higher credit risk), and thus, the CDS market enters a more volatile regime. To alleviate perceptions of systemic risk in the banking sector, the government intervenes by acquiring partly or fully the nearly-collapsed banks and re-capitalizes them. As the government effectively increases its share of non-performing assets, public finances deteriorate and consequently the bank's credit risk is transferred to the public sector (Attinasi et al. 2009). In a higher volatility regime, markets penalize fiscal imbalances more strongly than in a less volatile regime, notably before the collapse of Lehman Brothers (Von Hagen et al. 2011). In contrast to Alter and Schüler's (2012) research into individual countries' experiences, we argue that the private-to-public transfer of credit risk is also a characteristic at the level of the euro area. We expect that a positive change in both the level and the volatility of BCDS spread will be followed by a positive change in the level of SCDS spread.

2.2 The Balance-Sheet Hypothesis

Following Acharya et al. (2013), the weakening of public finances increases the probability of default on sovereign debt. As the probability of default increases, investors will require higher risk premium on investments in sovereign bonds. Higher risk premium depresses the sovereign bond market and impairs balance sheets of bond holders, mainly banks.

Hypothesis 2.1. A positive change in SCDS spread is followed by a positive change in BCDS spread.

In the extant literature, most researchers identify that government interventions mitigate the consequences of a systemic banking crisis, since credit risk is transferred to the public sector (Ejsing and Lemke 2011, Dieckman and Plank 2012). Therefore, following this argument, BCDS spread should decrease. Notwithstanding, this argument has received only a weak empirical support. Indeed, after the implementation of large-scale rescue packages provided by governments in the euro area to their national banking sectors in October 2008, BCDS spreads temporarily decreased, only to recuperate to its previous level soon after. However, the mechanism used to transfer risk from the banking sector to the sovereign issuers was constrained by the credibility of government contingent liabilities to the banking sector (Alter and Schüler 2012). Hence, we can now formulate the second part of this hypothesis.

Hypothesis 2.2. The response of BCDS spread to changes in SCDS spread is greater in a more volatile CDS market regime as opposed to a less volatile regime. [7]

In accordance with Kaminsky and Schmukler (2002) and Athanasoglu et al. (2014), who underscore the pro-cyclicality of sovereign debt rating and of the banking sector, an increase in the credit risk on sovereign debt will lead to a greater increase in the banking sector's credit risk through a reduction in the value of banks' assets and bank retrenchment in a more volatile CDS market regime. Historically, episodes of sovereign defaults that occurred in emerging market economies, notably in Ecuador and Russia, led to large losses in their national banking sectors (see also IMF 2002). In developed economies, stronger financial institutions amplify the adverse effects of sovereign defaults on financial intermediation by allowing domestic banks to boost leverage (Gennaioli et al. 2014 and Sandleris 2014).

2.3 The Expected Volatility Hypothesis

Hypothesis 3.1. Positive changes in the CDS spreads are followed by positive changes in the VSTOXX volatility index.

Unobservable firm's asset volatility can be approximated reasonably well by the VSTOXX volatility index, similar to Alexander and Kaeck (2008). An increase in the BCDS spread generates greater uncertainty and may delay investment decisions. Stock market investors may decide to rebalance their asset portfolios, and thus increasing exposure to stocks that are less dependent on bank lending. Additionally, the downgrading of sovereign bonds – that contributes to higher SCDS spread – can raise the cost of borrowing for governments. As a result, governments may offset the adverse budget effect of higher cost of borrowing through levying taxes on firms. The ensuing reduction in firms' future stream of

[7] Acharya et al. (2013) assert that a shock to the sovereign's credit risk should impact the financial sector's credit risk through three channels: (a) on-going bailout payments and subsidies, (b) direct holdings of sovereign debt and (c) explicit and implicit government guarantees.

profits is conducive to financial instability (Kaminsky and Schmukler 2002). Furthermore, an unfavourable change in sovereign rating that reflects an increase in the sovereign credit risk (Afonso et al. 2012) can aggravate financial instability (Afonso et al. 2014).

Hypothesis 3.2. The response of firm value volatility is greater in a more volatile credit default swap market regime as opposed to a less volatile regime.

Elevated volatility impairs informational contents of the credit default swap market and further raises uncertainty to firms and thus to stock market investors. Consequently, investors will demand higher risk premium in order to invest in stocks of companies that are heavily exposed to bank lending. Alternatively, the uncertainty surrounding future credit rating of sovereign bonds may exasperate expected firm value volatility. This hypothesis is supported by Calice and Ioannidis (2012) who document that the volatility of a bank's equity value is substantially higher when the CDS market is in a volatile regime.

2.4 The Risk Premium Hypothesis

Hypothesis 4.1. Positive changes in the CDS spreads are followed by negative changes in the EUROSTOXX stock index.

An increase in both BCDS and SCDS spreads signals economic hardship similar to Grammatikos and Vermeulen (2012). When BCDS spread increases, banks' bonds lose value and their yields increase to reflect higher cost of capital. As a result, future expected bank cash flows are discounted with a higher discount rate, while simultaneously the stock price decreases, as investors demand higher risk premium to compensate for the increased riskiness of the bank. Higher cost of capital is then transmitted to non-financial companies that rely on bank lending to finance their investment projects. With higher cost of capital, some investment projects become unprofitable and thus are discarded by the company. This places a constraint on the company's growth prospects, justifying a stock price decrease. Overall, an increase in the BCDS spread is followed by a decrease in the EUROSTOXX stock index. Similar to Vassalou and Xing (2004) and Sgherri and Zoli (2009) – who underline the importance of credit risk in the pricing of equities – Hypothesis 4.1 assumes that investors become increasingly concerned about the fiscal implications of the global financial crisis driving SCDS spread higher. Consistent with this hypothesis, Calice and Ioannidis (2012) find that bank returns of large complex financial institutions respond negatively to a positive shock to CDS spreads.

Hypothesis 4.2. When the CDS market enters a more volatile regime, the magnitude of the response of the EUROSTOXX stock index is greater than in a less volatile regime.

In accordance with Hypothesis 4.2, Norden and Weber (2004) find that (i) the CDS market is more sensitive to the stock market than the bond market; and (ii) the magnitude of this sensitivity is negatively related to a firm's average credit quality. Furthermore, downgrades of sovereign bonds can also manifest cross-security contagion effects on stock market returns during financial crises (see also Kaminsky and Schmukler 2002). Moreover, these downgrades trigger contagion effects on bank stock returns for those banks that investors expect to receive large government support (Correa et al. 2014).

3. The Methodology

In Section 3.1, we outline the model that is used in our empirical analysis. In Section 3.2, we describe the estimation method. In Section 3.3, we describe the impulse response functions.

3.1 The Model

We employ a Markov-Switching Bayesian Vector Autoregression (MSBVAR) model to study the regime-varying relation between BCDS and SCDS spreads. The MSBVAR model can be specified as

$$y_t = C_{s_t} + B_{1,s_t} y_{t-1} + \cdots + B_{P,s_t} y_{t-p} + G_{s_t} x_t + A_{s_t} u_t, s_t = 1, \dots S, \qquad (1)$$

where y_t is an N-dimensional vector of dependent variables, C_{s_t} is an N-dimensional vector of constants in regime $s_t = 1, .., S$, x_t is a K-dimensional vector of exogenous variables, B_{p,s_t} and G_{s_t} are (N x N) and (K x N) matrices of coefficients in regime s_t, respectively, and u_t is an N-dimensional vector of normally distributed structural disturbances uncorrelated at all leads and lags, where $p = 1, \dots, P$. The variance of each structural disturbance is normalized to unity. We assume that all parameters may switch among *S* regimes. The reduced-form disturbances are the structural disturbances pre-multiplied by a regime-dependent matrix A_{s_t}. Consequently, the variance and covariance matrix of $A_{s_t} u_t$ is also regime-dependent, as indicated in the following equation:

$$\Sigma_{s_t} = \mathrm{Var}\left(A_{s_t} u_t\right) = A_{s_t} I_N A'_{s_t} = A_{s_t} A'_{s_t} \qquad (2)$$

The regime s_t is assumed to follow a hidden *S*-state Markov-chain. The probability of being in regime j conditional on the current regime i is assumed constant. The conditional probabilities that span the *S* regimes are given by the following probability transition matrix P:

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1S} \\ \vdots & \ddots & \vdots \\ p_{S1} & \cdots & p_{SS} \end{pmatrix}, \qquad (3)$$

Where $p_{ij} = p(s_{t+1} = j | s_t = i)$ and $\sum_{j=1}^{S} p_{ij} = 1$ for all $i = 1, \ldots, S$.

For $t = 1, \ldots, T$, denote $Y_t = \{y_1, \ldots, y_t\}$. More compactly, Equation (1) can be written as

$$p(u_t | Y_{t-1}, x_t, s_t = i) = \mathcal{N}(0, \Sigma_i), \tag{4}$$

Where $\mathcal{N}(a_i, b_i)$ refers to the normal probability distribution function with mean a_i and covariance matrix b_i in regime i. The overall log-likelihood function $logp(y_T | x_T, \Phi)$ can be obtained by

$$logp(y_T \mid x_T, \Phi) = \sum_{t=1}^{T} logp(y_t | Y_{t-1}, x_t, \Phi), \tag{5}$$

where

$$p(y_t | Y_{t-1}, x_t, \Phi) = \sum_{i=1}^{S} p(s_t = i | Y_{t-1}, x_{t-1}, \Phi)\, p(y_t | s_t = i, Y_{t-1}, x_t, \Phi) \tag{6}$$

where is $p(y_t | s_t = i, Y_{t-1}, x_t, \Phi)$ is the probability density function of y_t conditional to regime i, and

$$p(s_t = i | Y_{t-1}, x_{t-1}, \Phi) = \sum_{s_{t-1}=j=1}^{S} p(s_t = i | s_{t-1} = j) p(s_{t-1} = j | Y_{t-1}, x_{t-1}, \Phi). \tag{7}$$

3.2 The Estimation Method

The optimization of Equation (5) may be performed by means of a suitable extension of an expectation-maximization (EM) algorithm described in Hamilton (1994, Chapter 22) and Krolzig (1997) or by means of a Bayesian estimation algorithm (see also Waggoner and Zha 2003, Sims and Zha 2004, Sims and Zha 2006, Sims et al. 2008, *inter alia*). In this research, we use a Bayesian inference based on a Gibbs sampler that belongs to the Markov Chain Monte Carlo (MCMC) family of algorithms. The Gibbs sampler is a recursive Monte Carlo simulation method that requires only knowledge of the full conditional posterior density of the parameters of interest. An advantage of a Bayesian estimator is that it takes into account the whole distribution available from Bayesian sampling, whereas an EM algorithm can only return a single point from the distribution. Thus, the Gibbs sampler can be viewed as a stochastic version of the EM algorithm[8].

3.3 The Generalized Impulse Response Functions

The Choleski decomposition is typically used in the literature to orthogonalize the reduced-form variance and covariance matrix Σ_i given in Equation (2).[9] Because this approach is not invariant to the ordering of the endogenous variables in the VAR, Pesaran

[8] A detailed description of the Gibbs sampler is available in Appendix B.

[9] The Choleski decomposition provides an indirect estimate of the lower triangular matrix A_i. Underlying the triangular factorization is the identification scheme proposed by Sims (1980), who suggests obtaining a unique triangular factorization of the residuals of a reduced-form VAR model by imposing a specific ordering of the endogenous variables of the VAR model.

and Shin (1998) propose an alternative approach that does not have this shortcoming, based on the so-called generalized impulse response functions (GIRFs). Pesaran and Shin (1998) show that for a non-diagonal variance and covariance matrix, the orthogonalized and the generalized impulse responses coincide only in the case of the impulse responses of the random disturbances to the first equation of the VAR. Against this background, we use the generalized impulse response analysis.

The contemporaneous and lagged response of the endogenous variable can be measured by means of the regime-dependent GIRFs. In practice, vectors of the regime-dependent impulse-responses can be derived by combining the parameter estimates of the unrestricted MSBVAR with the estimate of the regime-dependent variance and covariance matrix Σ_i. Let's first assume that in period 0, a shock hits the nth endogenous variable. Then, the contemporaneous response vector measures the impact effect of the nth random disturbance on the endogenous variables in period 0. A one standard deviation shock to the nth endogenous variable can be denoted as a vector of zeros except for the nth element, which is unity, i.e., $u_0 = (0, \dots, 0, 1, 0, \dots, 0)$. Pre-multiplying this vector by the estimate of the regime-dependent variance and covariance matrix $\hat{\Sigma}_i$ yields the contemporaneous response vector. A one-step-ahead response vector can be obtained by solving forward for the endogenous variables in Equation (1). It measures the impact effect of the nth random disturbance (that occurred in period 0) on the endogenous variables in period 1. Analytically, the contemporaneous and τ-step-ahead response vectors are given in Equations (8) and (9), respectively:

$$\hat{\psi}_{n,i,0} = \sigma_{nn,i}^{-1/2} \hat{\Sigma}_i u_0 \tag{8}$$

$$\hat{\psi}_{n,i,\tau} = \sigma_{nn,i}^{-1/2} \sum_{j=1}^{min\{\tau,p\}} B_{ji}^{\tau-j+1} \hat{\Sigma}_i u_0, \tau > 0 \tag{9}$$

It should be noted that Equations (8) and (9) depict *net* GIRFs, i.e., they assume that there are no further random disturbances in subsequent periods. However, because the BCDS and the SCDS spreads, the VSTOXX volatility index and the EUROSTOXX stock market index feature a slowly moving component and thus follow a high memory process, which is likely to be non-stationary, we transform the endogenous variables in *first differences*. To measure the responses of the endogenous variables in levels, *accumulate*d GIRFs are utilized, which can be obtained by adding up *net* GIRFs. It is evident that the contemporaneous accumulated response vector can be still measured by Equation (8). The τ-step-ahead accumulated response vector is given by Equation (10):

$$\tilde{\psi}_{n,i,\tau} = \sum_{j=1}^{\tau} \hat{\psi}_{n,i,j}, \tau > 0 \tag{10}$$

The long-run response accumulated response is obtain as $\tilde{\psi}_{n,i} = \lim_{\tau\to\infty} \tilde{\psi}_{n,i,\tau}$. Then, the long-run differential effect of nth random disturbance on mth endogenous variable in regime $i+1$ relative to regime i is given by

$$d\tilde{\psi}^m_{n,i+1} = \tilde{\psi}^m_{n,i+1} - \tilde{\psi}^m_{n,i} = \lim_{\tau\to\infty} \tilde{\psi}^m_{n,i+1,\tau} - \lim_{\tau\to\infty} \tilde{\psi}^m_{n,i,\tau} \quad (11)$$

Equation (11) allows testing if the long-run impulse response of mth endogenous variable to nth random disturbance is significantly different across regimes 1 through S. An advantage of focusing on the *long-run* GIRF is that its standard error becomes irrelevant, and statistical inference relies merely upon the value of the GIRF, rather than on the ratio of its value to the standard error, which driven by an arbitrarily chosen number of periods after the shock. Building upon the hypotheses outlined in Section 2, the magnitude of the impulse-response is greater in a more volatile regime.[10] Therefore, we have:

$$H_0: d\tilde{\psi}^m_{n,i+1} = 0 \text{ against } H_1: d\tilde{\psi}^m_{n,i+1} > 0 \quad (12)$$

4. Data

In the empirical analysis, we use daily data on banks' (iTraxx Senior Financials) and sovereign (iTraxx Sovereign Western Europe) CDS spreads, EUROSTOXX stock market index and VSTOXX volatility index, and the fixed-for-floating euro interest rate swaps for maturities ranging from 1 to 30 years. The data are retrieved from Thomson Datastream. The sample period spans 22/03/2005 – 21/06/2013, containing a total of 2154 daily observations. Most iTraxx CDS indices are traded for maturities of 3, 5, 7 and 10 years, with the 5 year maturity being the most liquid, and thus employed in this study. The iTraxx CDS indices are spread based indices and are quoted in the market in spread terms. The spread equates to an upfront price given the fixed deal spread (coupon) for the swaps. This price is essentially the upfront value of entering into a CDS index contract. In addition, we use the EUROSTOXX stock market index and the VSTOXX volatility index. Credit spreads (Fama and French 1989), default probabilities and recovery rates (Altman et al. 2005, Hackbarth et al. 2006, Pesaran et al. 2006), and investors' risk aversion (Annaert et al. 2013) tend to vary over the business cycle. Therefore, the business cycle should affect credit spreads through two channels: (i) the business-cycle vulnerability of default risk and (ii) time-varying investors' risk aversion that is incorporated in the risk premium of investment (Collin-Dufresne et al.

[10] It should be nevertheless noted that MCMC standard errors, estimated by means of the Gibbs sampler, make it possible to test the null hypothesis in Equation (12) at the 95% confidence level by graphically inspecting the position of the GIRF and the 2-standard error confidence bands. The estimated GIRF are presented and analysed in Section 5.2.

2001). We follow Collin-Dufresne et al. (2001) and Annaert et al. (2013) by including a market wide stock index return as a control variable for the business climate. The EUROSTOXX stock index is a broad index that represents large, mid and small capitalisation companies of 12 euro zone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

The VSTOXX volatility index is based on EUROSTOXX real-time option prices and is designed to reflect the market expectations from near-term up to long-term volatility. It is thought to represent market uncertainty of the economic prospects (Annaert et al. 2013) and time-varying investors' risk aversion (Pan and Singleton 2008). Alternatively, it may also represent market strains that limit capital mobility across different market segments and thus sustain temporarily high risk premia (Annaert et al. 2013). Following Alexander and Kaeck (2008) and Annaert et al. (2013), we use the VSTOXX volatility index to measure market-wide volatility expectations.

Finally, fixed-for-floating euro interest rate swaps capture the risk free interest rate and expectations of the future risk free interest rate. Higher risk free interest rate will incentivize investors to invest in risk free assets, thereby decreasing the share of risky assets in their portfolio and decreasing the credit risk. In the risk neutral world, the risk free interest rate constitutes the drift (Merton 1974). Hence, an increase in the risk free interest rate drives up the risk neutral drift and decreases the probability of default. Following Alexander and Kaeck (2008), we calculate the first and second principal components on the fixed-for-floating euro interest rate swaps for maturities ranging from 1 to 30 years. The first principal component captures the level of the risk-free interest rate, whereas the second component ("slope") represents expectations of future movements in the risk free interest rate.[11]

– Please Insert Table 1 about here –

Panel A (Panel B) of Table 1 summarises descriptive statistics of the variables in levels (in first differences). Over the sample period, the mean of the BCDS spread (106.87 basis points) is greater than the mean of the SCDS spread (91.79 basis points) reflecting a greater credit default risk of the European banking sector. BCDS also is more volatile than SCDS, as witnessed by the range of variation of the data (the difference between the minimum and maximum values) and by the standard deviation. BCDS deviates from the

[11] Moreover, the slope of the term structure conveys valuable information about the business cycle stance (Estrella and Mishkin 1997). Specifically, a high slope anticipates an increase in future economic activity (Fama 1984, Estrella and Hardouvelis 1991). It should also be noted that the use of the level and slope interest-rate swaps is consistent with the literature advocating that co-movement between banks' and sovereign issuers' CDS premia may be driven by a common set of unobserved factors, probably reflecting changing macroeconomic fundamentals (Ejsing and Lemke 2011, Acharya et al. 2013).

mean on average by 81.99 basis points, whereas SCDS deviates by only 49.58 basis points. The two measures of credit default risk are also positively skewed and leptokurtic. The resulting distributions are non-normal, since the normality is rejected by the Jarque-Bera test statistic. The change in the VSTOXX volatility index has a positive mean, suggesting that expectations of stock market volatility increase over the sample period. It experienced significant fluctuations over the sample period, as indicates the range of variation in the standard deviation. The latter indicates that the change in the VSTOXX volatility index deviates from the mean on average by 1.93 index points. The change in the volatility index is also positively skewed and highly leptokurtic resulting in a non-normal distribution of values. Daily percentage stock returns were negative during the sample period (-0.0032% in daily percentage). Stock returns were highly volatile, as suggests the range of variation and the standard deviation. The latter reveals that stock returns deviate from the mean on average by 1.42%. Consistent with empirical evidence on skewness and kurtosis, returns are negatively skewed and leptokurtic, implying that big negative events in the European stock market are more likely than big positive events and that the density of returns is greater the closer returns are to the sample median. Therefore, the resulting distribution of returns is non-normal. The fixed-for-floating interest rate swaps have positive means ranging from 2.25% (1-year maturity) to 3.76% (20-year maturity). Thus, longer maturity interest rate swaps tend to have a higher rate than shorter maturity interest rate swaps. The converse is true for the range of variation and the standard deviation. Longer maturity interest rate swaps tend to be less volatile. Shorter maturity (up to 4 years) swaps are positively skewed, whereas longer maturity swaps are negatively skewed. Interest rate swaps are leptokurtic and non-normally distributed for all maturities.

– Please Insert Table 2 about here –

Table 2 summarizes results for the unit root tests. We use four different unit root tests – the Augmented Dickey-Fuller (ADF) test, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, the Phillips-Perron (PP) test and the Zivot-Andrews (ZA) test – to test for a unit root in the data.[12] In particular, Table 2 provides overwhelming evidence that the EUROSTOXX stock index, SCDS spread and interest rate swaps for maturities higher than 2 years have a unit root. The null hypothesis of a unit root is rejected for the BCDS spread and SLOPE if the

[12] The choice of the tests is based on the fact that (i) the ADF and PP tests are classical parametric and semi-parametric unit root tests, respectively; (ii) the ADF, PP and ZA tests hypothesize a unit root as a null hypothesis, whereas the KPSS test hypothesizes no unit root as a null hypothesis and hence aims at complementing the classical unit root tests; and (iii) unlike the other three tests, the ZA tests allows for the possibility of a break in the series that may contaminate the power of the classical unit root tests.

ZA test is used. Further, the VSTOXX volatility index is identified as difference-stationary only if the KPSS test is used. In general, the results of the unit root tests support the use of variables in first differences in the MSBVAR models. Because interest rate swaps for most maturities have a unit root, we run a principal component analysis on the series in first differences.

– Please Insert Table 3 about here –

Table 3 summarizes the coefficients of pairwise correlations among the endogenous and exogenous variables in first differences. Specifically, the BCDS and SCDS spreads are positively correlated with the VSTOXX volatility index. The EUROSTOXX volatility index is negatively correlated with the other endogenous variables. With regard to the correlations between endogenous and exogenous variables, the BCDS and SCDS spreads, and the VSTOXX volatility index (EUROSTOXX stock index) exhibit a moderate negative (positive) association with interest rate swaps of different maturities.

5. Empirical Findings

In Section 5.1, we describe the regimes identified by means of the MSBVAR model. In Section 5.2, we analyze the estimated effects of endogenous variables by means of impulse response functions. In Section 5.3, we study the estimated effects of exogenous variables. In Section 5.4, we report robustness checks.

5.1 Markov Regimes

Key to the MSBVAR model is the identification of switching regimes, governed by a stochastic, unobserved regime variable s_t. The regimes are associated with different conditional distributions of the BCDS and the SCDS spreads, the change in the VSTOXX volatility index and returns on the EUROSTOXX stock market index driven by s_t. The regime-dependent parameter matrix Φ_i is estimated using the Gibbs sampler, and the probability of each regime (and thus the length of each regime) is endogenously determined. However, the number of regimes s is based on the notion that the dynamic relation between the BCDS and SCDS spreads may be (i) different before and after the subprime-mortgage crisis period (i.e., July 2007), and (ii) different in periods clustered around the various credit events after the subprime mortgage crisis – such as the contagious effects of the collapse of Lehman Brothers – and in periods where those contagious effects deteriorated. Therefore, a parsimonious model that assumes two regimes may fail to distinguish between periods wherein bond investments are highly risky – characterized by uncertainty and volatility – and periods where the riskiness of bond investments is perceived as less critical[13]. Thus, assuming two regimes only, it is possible to omit a portion of relevant information from our empirical analysis and hence the model will become overly restrictive.

Moreover, a model with 2 regimes is likely to lead to misspecification issues when the true number of regimes is in fact higher. Furthermore, our choice for the number of Markov regimes is further supported by Chib's (1995) method and the method of bridge sampling, proposed by Meng and Wong (1996) and extended by Frühwirth-Schnatter (2004). We employ 5000 MCMC draws from a posterior density to compute the marginal log-likelihood values that used to select among various models differing in the number of regimes of the hidden latent variable. Results of Chib's (1995) and Meng and Wong (1996) methods for four Markov regimes for the four dependent variables are summarized in Table 4. From this table, we observe that the marginal log-likelihood values increase substantially from one to three regimes but then decrease in regime four for all dependent variables. Both Chib's and the bridge-sampling methods suggest that a model with three Markov regimes fits the data best.[14]

– Please Insert Table 4 about here –

We use a MSBVAR model of order 1 to estimate the relation between the BCDS and SCDS spreads, returns on the EUROSTOXX stock index and the change in the VSTOXX volatility index. The vector of exogenous variables comprises the first ("level") and second ("slope") principal components on the fixed-for-floating Euro interest rate swaps for different maturities (from 1 year to 30 years). All parameters are allowed to change across the regimes. The variance and covariance matrix is also regime-dependent. The smooth-estimated regime probabilities are presented in red Panels A – C of Figure 2 (bottom plot).

– Please Insert Figure 2 about here –

A regime is defined as a region (or polygon) with the highest smoothed probability, i.e.

$$s_t = i^* = arg\,\max_i p(s_t = i|Y_T, X_T, \Phi) \qquad (13)$$

The estimation results reported in Figure 2 suggest that regime 1 prevails from the beginning of the sample (March 2005) till July 2007 that marks the beginning of the U.S.

[13] The choice of the number of regimes has been fiercely debated in the literature. A standard approach is to use 2 regimes (e.g., high and low volatility regimes in financial markets), based on economic rather than on statistical principle. However, it is not uncommon to rely upon a more complex three-regime MSBVAR. An example is Artis et al. (2004) who identify three regimes (recessions, moderate-growth periods and high-growth periods) in the post-war US business cycle.

[14] While our main analysis is based on a MSBVAR that assumes the presence of three regimes, we also estimate a MSBVAR with two regimes.The results of the 2-regime MSBVAR model are not presented but are briefly discussed in Section 5.5.

subprime mortgage crisis. Since the BCDS and SCDS spreads feature a slowly moving component with a negative tendency, regime 1 can be viewed as a low volatility regime. In July 2007, the CDS market switches from regime 1 to regime 2. This regime can be viewed as a collection of sub-periods where the BCDS and SCDS spreads are more volatile than in regime 1, but less abrupt than in regime 3. Regime 2 dominates the rest of the sample period that starts in July 2007 and is only occasionally interrupted by regime 3, when the BCDS and SCDS spreads depict an accelerated increase and decrease with a turning point in the middle of the regime. Thus, regimes 2 and 3 can be denoted as intermediate volatility and high volatility regimes, respectively.

5.2 Endogenous Variables

The main findings are summarized by means of the GIRF (Pesaran and Shin 1998). The GIRFs for the four shocks are depicted in Panels A – D of Figure 3. Panel A (B, C, D) presents the response of the four endogenous variables to a shock to the BCDS spread (SCDS spread, return on the EUROSTOXX stock index, change in the VSTOXX volatility index) in the three regimes. The GIRFs are analyzed in terms of the long-run differential pairwise effects across the three regimes, outlined in Section 3.3.

Panel A suggests that an unexpected change in the BCDS spread has a positive effect on the BCDS and the SCDS spreads, and the VSTOXX volatility index. On the other hand, it exerts a negative effect on the EUROSTOXX stock index.

– Please Insert Figure 3 Panel A about here –

A rise in BCDS spread signals an increase in credit risk in the banking sector. As euro area governments extend guarantees to their national banking sectors, a positive effect on the SCDS spread is expected. Indeed, as the credit risk in the euro area banking sector increases, government liability increases too. In line with our expectations, the impulse response is clearly positive and significant, and it substantially varies across the regimes. More precisely, in the low volatility regime the response is smallest in magnitude, whereas in the high-volatility regime the response has the largest magnitude. Consistent with Alter and Schüler (2012, Hypothesis 2(a)), following government interventions, changes in the banking sector's credit risk affect the sovereign credit risk more strongly than before, since governments take over liabilities of the banking sector. Gerlach et al. (2010) argue that sovereign credit risk may be affected by the banking sector by two channels. The first channel refers to the probability that the government can recapitalize banks with public money if they run into financial difficulties. The second channel, identified by Adrian and Shin (2009), underscores the importance of financial intermediaries' balance sheet adjustments for aggregate liquidity and financial stability for the government's fiscal position, public revenue and spending.

Second, a change in BCDS spread also causes a positive and permanent effect on the level of the BCDS spread. Although the autoregressive component in the equation for BCDS spread is not justified on theoretical grounds, it captures the share of variation in the change of BCDS spread that is not explained by the predetermined and exogenous variables in the VAR.[15] Third, the impulse response of the VSTOXX volatility index is positive, and it increases with positive changes in the banking sector's credit risk.[16] This allows us to consider the VSTOXX volatility index as a proxy to capture spikes in volatility. Similar to Alexander and Kaeck (2008), our results imply that unobservable firm's asset volatility can be approximated and captured by the VSTOXX volatility index. Indeed, an increase in BCDS spread generates greater uncertainty and volatility spikes in the stock market, while also it distresses investments. Consequently, stock market investors may decide to rebalance their portfolios of assets by increasing exposure to stocks of non-financial companies that are less affected by increasing banks' credit risk.

Fourth, the impulse response of the EUROSTOXX stock index is negative and significant. Indeed, as an increase in BCDS spread generates greater uncertainty to firms, the risk premium required by stock market investors increases. Thus, investors require lower valuations in order to invest in portfolio of stocks. Therefore, the impulse response of the EUROSTOXX stock index has the expected negative sign. The impulse response also has a regime-dependent pattern, wherein the response in the high volatility regime is greater than the response in the low and intermediate volatility regimes. This finding implies that deterioration in credit risk conditions and an increase in uncertainty, render stock market investors more vulnerable to news about the banking sector's credit standards.

To sum up, Panel A of Figure 3 is supportive of Hypotheses 1, 3 and 4. An unanticipated change in BCDS spread has a direct effect on BCDS and SCDS spreads and the VSTOXX volatility index, and it has an inverse effect on the EUROSTOXX stock index. Crucially, an unanticipated change in BCDS spread has always a stronger effect in a more volatile than in a less volatile regime.

[15] The autoregressive component is empirically motivated by Byström (2005, 2006), who finds that iTraxx Europe indices feature a significant autocorrelation in their spread.

[16] The impulse response is significant in the intermediate and high volatility regimes. The VSTOXX volatility index is based on the current value of stock options. It can be thought of as a forward-looking measure of stock market volatility and measures uncertainty of stock market investments.

Panel B of Figure 3 suggests that an unanticipated change in the SCDS spread has a positive effect on BCDS and SCDS spreads, and the VSTOXX volatility index. More concretely, an increase in the spread triggers negative movements on the EUROSTOXX stock index whilst also, an increase in SCDS spread signals greater perceived risk of sovereign bonds. The impulse response of BCDS spread is positive, significant and regime dependent. The effect of a change in SCDS spread is relatively smaller in the low volatility regime, but its magnitude grows in the intermediate volatility regime. Finally, the magnitude of the effect amplifies in the high volatility regime, which mainly clusters in the period spanning from October 2008 – March 2009. Specifically, the period around October 2008 is marked by various important credit events in the euro area that triggered the introduction of government rescue packages. Following government interventions in 2008, BCDS spread initially decreased but then they recovered, as the mechanism used to transfer credit risk from the banking sector to sovereign issuers was constrained by the credibility of government contingent liabilities to the banking sector. This result is supported by Alter and Schüler (2012) who argue that "due to changes in the composition of both banks' and sovereign balance sheets… the government CDS spreads have increased importance in the price discovery mechanism of the banks' CDS series".

– Please Insert Figure 3 Panel B about here –

Second, we corroborate the works of Byström (2005, 2006) by identifying that an unanticipated change in the SCDS spread has a positive and permanent effect on the level of SCDS spread. The sign and significance of the impulse response function of SCDS spread can be justified on empirical grounds, since spread changes feature a positive and significant autocorrelation. The impulse response is smaller in magnitude in a lower than in a higher volatility regime.

Third, the impulse response of the VSTOXX volatility index is positive and significant, and it shows a regime-dependent pattern. An increase in SCDS spread triggers an increase in the economic risk. Particularly, the euro area governments' fiscal position is weakened by the introduction of large-scale financial rescue packages for their national banking sectors. This development depresses the governments' fiscal position and causes a gap between public spending and revenues (Acharya et al. 2013). As a result, uncertainty among stock market investors soared. Fourth, the impulse response of returns on the EUROSTOXX stock index is negative and significant, while also it varies across the three regimes. This result is intuitively in line with Grammatikos and Vermeulen (2012), who find that euro area returns on non-financial and financial companies become increasingly (negatively) dependent upon the Greek SCDS spread in the period following the collapse of Lehman Brothers. A rise in sovereign debt due to the countercyclical fiscal policy measures, is perceived by stock market investors as a burden on economic growth prospects. Slower economic growth and expectations for an increase in tax rates undermine corporate profits and lead to a decrease in stock market returns. To summarize, Panel B of Figure 3 confirms and supports Hypotheses 2, 3 and 4. An unanticipated change in SCDS spread has a direct effect on BCDS and SCDS spreads and the VSTOXX volatility index, and an inverse effect on the EUROSTOXX stock index. An unanticipated change in the SCDS spread has always a stronger effect in a more volatile than in a less volatile regime.

Panel C of Figure 3 suggests that an unanticipated change in the VSTOXX volatility index has a positive effect on BCDS and SCDS spreads, and the VSTOXX volatility index. On the contrary, it exerts a negative effect on the EUROSTOXX stock index. We find that an increase in the VSTOXX volatility index leads to a significant increase in BCDS and SCDS spreads. This effect is always larger in magnitude in a higher volatility regime. This result is in line with Alexander and Kaeck (2008), who find that higher firm value volatility is more likely to hit a default barrier than lower firm value volatility. Second, we also document that an unanticipated change in the VSTOXX volatility index triggers a direct permanent change in the index level. This effect is larger in magnitude in a higher volatility regime. Third, as expected, higher firm value volatility feeds into higher risk premium that is required by stock market investors. In a higher volatility regime this effect is larger in magnitude, depressing further stock market returns. This explains a negative impulse response of the EUROSTOXX stock index.

– Please Insert Figure 3 Panel C about here –

Panel D of Figure 3 indicates that an unanticipated change in the EUROSTOXX stock index has a negative effect on BCDS and SCDS spreads, and the VSTOXX volatility index. In particular, we observe that when a firm's value depreciates, the probability of default will increase as the firm may not be able to honor its credit commitments. On the one hand, this increases firm's value volatility, which is represented by a change in the VSTOXX volatility index. On the other hand, the loan default rates increase in the economy as the leveraged firm may not be able to repay its loans. This impairs the performance of banks and spills over to the CDS market. As a result, when the decrease in firm's value becomes widespread, BCDS and SCDS spreads increase. These results are consonant to some extent with Alexander and Kaeck (2008) who document that a change in a firm's value has an inverse effect on CDS spreads.

– Please Insert Figure 3 Panel D about here –

5.3 Exogenous Variables

The impulse-response functions can be used to evaluate the effects of shocks to endogenous variables only. However, they do not capture the effects of the first and second principal components that are used as exogenous variables in our research. To evaluate the above theoretical underpinnings, the estimated effects of the first and second principal components in Panel A of Table 5 can be analyzed.

– Please Insert Table 5 about here –

The first (second) principal component can be interpreted as the "level" ("slope") of a risk-free interest rate. An increase in the risk-free interest rate renders risk-free assets (e.g. government bonds) more attractive and, therefore, banks will rebalance their portfolios of assets selling off risky investments and buying safer government bonds. This finding agrees with Collin-Dufresne et al. (2001), Alexander and Kaeck (2008) and Chan and Marsden (2014). As a result, BCDS spread will decrease, indicating a negative association between the first principal component and BCDS spread. Because the scenario involving government interventions in healthy banks can be ruled out, we would also expect a negative association between SCDS spread and the first principal component.

Regarding the second principal component, higher term structure incentivizes banks to invest in longer-term government securities and, hence, decreases BCDS and SCDS spreads. In this respect, our results endorse Alexander and Kaeck (2008). The first principal component is negative and significant implying that changes in interest rates influence inversely BCDS and SCDS spreads. Furthermore, the second principal component should have a negative association with BCDS and SCDS spreads but there is no significant evidence to support this assertion.

5.4 Robustness Checks

Our main findings are supported by several robustness checks. First, following Alexander and Kaeck (2008), we replace the first and the second principal components with the 5-year interest rate swap ("LEVEL") and difference between 10 and 2 year interest rate swaps ("SLOPE"), respectively. Panel D of Table 5 indicates that the effects of the alternative measures of interest rate level and slope are qualitatively similar to the effects of the first and second principal components. In particular, we find that the 5-year interest rate swap has in general a negative and significant effect on BCDS and SCDS spreads. Our results also suggest that the alternative measure of slope in general does not appear to influence significantly the BCDS and SCDS spreads.[17]

Second, we replace the EUROSTOXX stock index by the EUROSTOXX 50 index in our MSBVAR model. The EUROSTOXX 50 is Europe's leading Blue-Chip index that represents 50 leading super-sector stocks in the euro area. In analogy with our results obtained using a broader EUROSTOXX stock index, the regime-dependent GIRFs indicate that the an unexpected change in the BCDS, SCDS spreads and in the VSTOXX volatility index has always a negative effect on the EUROSTOXX 50 stock index. Furthermore, the response of the EUROSTOXX 50 stock index is always greater in magnitude in a more volatile regime.

Third, motivated by Correa et al. (2014) and Gennaioli et al. (2014), who investigate the effects of sovereign defaults on bank credit and bank stock returns, we substitute the EUROSTOXX stock index with the EUROSTOXX BANKS index comprising 30 largest banking sector's stocks. This exercise corroborates the results obtained using broader and more diversified stock market indices in the euro area.

Fourth, we estimate a MSBVAR model of order 4 (MSBVAR(4)). This lag length is selected by the Akaike Information Criterion (AIC) on a linear VAR. The results obtained using the MSBVAR(4) are qualitatively similar to the MSBVAR(1). Fifth, we estimate the MSBVAR model with 2 regimes. This model implies that a low volatility regime (regime 1) dominated in the sample sub-period before July 2007, and a high volatility regime (regime 2) dominated thereafter. The results obtained from this model are qualitatively similar to the results obtained using the MSBVAR model with 3 regimes. The 2-regime MSBVAR shows that the effects of shocks to the credit default swap market and the stock market are always greater (in absolute value) in the high volatility regime than in the low volatility regime. This finding is further corroborated by the 2-regime MSBVAR estimated on weekly data.

Fifth, since the VSTOXX volatility index shows some tendency to revert to the mean we also estimate a 3-regime VAR, with the VSTOXX volatility index measured in levels. The effects of shocks to the BCDS and SCDS spreads, EUROSTOXX stock index and VSTOXX volatility index resemble those reported in Figure 3 and described in Section 5.2. A shock to the VSTOXX volatility index has a positive effect on the BCDS and SCDS spreads,

[17] Due to the presence of a unit root, the 5-year interest rate swap is used in first differences. The difference between the 10-year and 2-year interest rate swaps is stationary (features a unit root) according to the Zivot-Andrews (ADF, KPSS and PP) test. In Panel D of Table 5, the slope is measured in levels. As a robustness check, we also estimated our MSBVAR models with a slope measured in first differences. Results are qualitatively similar to those obtained using the measures of level and slope. The results using the measure of slope in first differences are not reported, but are available from the authors upon request.

the VSTOXX volatility index, and it has a negative effect on the EUROSTOXX stock market index. Moreover, this effect is greater in a more volatile regime. The detailed results obtained for our second through sixth robustness checks are not reported but are available from the authors upon request.

6. Conclusion

This study examines the regime-dependent interdependence between euro area banks' and sovereign credit default swap (BCDS and SCDS, respectively) spreads, stock and credit markets via using a state-of-art MSBVAR model. The model sheds light on a significant regime-dependent interdependence between these variables. Specifically, our results indicate that government interventions in the banking sector metastasize and lead to credit risk transfer from the banking to the public sector. Furthermore, the results assert the feedback hypothesis, while also imply that the expectation of support from national governments allows banks to be more leveraged, making them more vulnerable to sovereign defaults. Therefore, this study provides novel evidence that large-scale rescue packages do not necessarily stabilize the banking sector, as witnessed by rising BCDS spreads. The increase in BCDS spreads and the subsequent decision of euro area governments to bail out troubled banks triggered an unprecedented increase in SCDS spreads. This decision resulted in greater fiscal deterioration of euro area countries and thus in greater sovereign credit risk (IMF 2013).

We also investigate the regime-dependent relation between the euro area credit and stock markets. According to Sandleris (2014), such interconnectedness builds upon two intertwined channels through which a sovereign default affects stock markets. First, a sovereign default can trigger a contraction in the credit market (credit channel). Moreover, in the event of a sovereign default, a decrease in investments affects negatively firms' net worth and makes collateral constraints more stringent (investment channel). The interaction and synchronicity between these two channels makes it important to incorporate stock market variables in our study. In response to the issues raised in the introduction, the empirical results provide strong evidence that an unexpected positive change to BCDS and SCDS spreads causes an increase in investors' expectations of stock market volatility, as measured by the change in the VSTOXX volatility index, and advances to a decrease in the EUROSTOXX stock index. In particular, we document a significant rise in co-movement in the post-bailout period between BCDS and SCDS and the VSTOXX volatility index. These findings are supported by the empirical evidence on the effects of changes in sovereign credit ratings on financial instability (Kaminsky and Schmukler 2002) and stock market returns (Brooks et al. 2004, Correa et al. 2014).[18] Moreover, we find that the effects of unexpected changes to BCDS and SCDS spreads on the VSTOXX volatility index and on the EUROSTOXX stock index are more pronounced and stronger in a more volatile regime, reflecting an increased incidence of contagion across financial markets.[19] Thus, our research provides also scope for hedging strategies for investments in the Euro Area CDS market. Indeed, stock market variables, such as the VSTOXX volatility index and the EUROSTOXX stock market index futures can be used to hedge against undesired developments in the BCDS and SCDS spreads.

Furthermore, we complement the literature that studies the determinants of BCDS and SCDS spreads. Whereas most of this literature uses *single-equation* models to evaluate the determinants of CDS (Alexander and Kaeck 2008, Chan and Marsden 2014), our research is based on a multiple-equation model. More concretely, we use a state-of-art Markov-Switching Bayesian Vector Autoregression (MSBVAR) model that (i) relaxes the assumption maintained in previous research that stock market variables are exogenous in determining CDS spreads, (ii) allows to compute regime-dependent impulse response functions, as in Erhmann et a. (2003) and (iii) uses a Gibbs sampler to estimate the MSBVAR, which can be thought of a stochastic version of the expectations maximization algorithm commonly used to estimate Markov-switching models.[20] Our study extends previous research in terms of the data sample and the number of regimes. Specifically, Alexander and Kaeck (2008) use a Markov-switching model to identify two regimes, and their sample period spans three years of daily data, from 06/2004 through 06/2007. By contrast, we use daily data from 03/2005 to 06/2013. Moreover, a low volatility regime, identified by our MSBVAR model, encompasses the entire sample period used in Alexander and Kaeck (2008). In addition, by means of smoothed regime probabilities, we also identify an intermediate volatility regime that started

[18] If bank bailouts contribute to instability of financial markets, and sovereign credit rating downgrades have a larger effect on bank equity returns for those banks that are more likely to receive support from their governments, then investors will be willing to buy bank equity only if its valuation is sufficiently low in periods marked by heightened volatility. Admittedly, changes in sovereign credit ratings can simultaneous influence both the CDS market and the stock market, thus generating a co-movement between SCDS spread, stock market returns and volatility.

[19] The effects of unexpected changes to BCDS and SCDS spreads on the VSTOXX volatility index and on the EUROSTOXX stock index are more pronounced and stronger in a more volatile regime, reflecting an increased incidence of contagion across financial markets. Following Yuan (2005) and Jotikasthira et al. (2012), uninformed rational investors are not able to distinguish between selling based on liquidity shocks and selling based on fundamental shocks. Thus, when investors suffer a large loss, they are forced to liquidate their positions in other investments, triggering cross-market portfolio rebalancing. This finding complements Jorion and Zhang (2007) who examine contagion channels between CDS and stock markets.

[20] The Gibbs sampler has been seldom used to estimate Markov-switching vector autoregression models. Hamilton and Owyang (2012) is an example.

in July 2007 (and coincided with the beginning of the subprime mortgage crisis in the United States), and a high volatility regime that prevailed in the aftermath of extensive government interventions in September 2008.

We document that since July 2007, the CDS market switched from low risk (regime 1) to mainly intermediate (regime 2) and occasionally to high risk regime (regime 3). The transition from low to higher volatility regimes after 2007 indicates that the euro area switched from a period of low sovereign credit risk to that of unprecedented risk disintegration, because the economic crisis affected disproportionally the ‘periphery’ economies, compared to the ‘core’ German economy. Second, an unanticipated increase in stock market volatility increases bank and sovereign CDS spreads. Third, a decline in the EUROSTOXX raises equity market volatility, sovereign and bank CDS spreads. Finally, we provide novel evidence that the effects accelerated during, mainly, intermediate (regime 2) and high risk regime (regime 3). Hence, our research extends Acharya et al. (2013) by documenting that the two-way effects between banking and sovereign credit risks are stronger in a more volatile regime.

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Appendices

Appendix A. Credit Default Swaps

Credit default swaps (CDS) are derivative contracts that allow investors in an underlying debt instrument to protect themselves against a deterioration of credit quality and even a default on debt. As its name suggests, the payoff on a CDS depends on the default of a specific borrower, such as a government or a firm, or of a specific security, such as a bond. The value of this instrument is especially sensitive to the state of the overall economy. For instance, if the economy moves toward a recession, the likelihood of defaults increases and the expected payoff on credit default swaps will rise quickly. The credit default swap was pioneered by JP Morgan in 1994.

In addition to the above, a CDS can be viewed as an insurance contract that provides protection against a specific default. CDSs are not traded on an exchange, however most CDSs are documented using standard forms drafted by the International Swaps and Derivatives Association (ISDA). CDS contracts provide protection against the default of a corporation, sovereign nation, mortgage payers, and other borrowers. The buyer of protection makes periodic payments, analogous to insurance premiums, at the CDS rate specified in the contract. If the named borrower defaults, the seller of protection must pay the difference between the principal amount covered by the CDS and the market value of the debt. For instance, when Lehman Brothers defaulted, its debt was worth about eight cents on the dollar, hence sellers of protection had to pay about ninety-two cents for each notional dollar of debt they had guaranteed. Following a credit event in a constituent of the index, the ISDA Determinations Committee votes to decide if a credit event has occurred for the entity and if an auction for the defaulted entity is to be held. If the outcome of this vote is positive, Markit publishes a new version of the index zero weighting the relevant entity i.e. the “reduced” index. Recovery rates for the examined indices are 40%. The benchmark Markit iTraxx Senior Financials index consists of 25 equally-weighted large and systemically important European banks.

Although CDSs can be used as insurance against a default, the buyer of protection is not obliged or required to own the named borrower’s debt or to be otherwise exposed to the borrower’s default (i.e. “naked” position). After two counterparties agree on the terms of a CDS, they can “clear” the CDS by having the clearinghouse stand (e.g. the International Exchange Clear Europe unit) between them.

Appendix B. Bayesian Updating and Gibbs Sampling

B.1 Bayesian Updating

The probability $p(s_{t-1} = i|Y_{t-1}, x_{t-1}, \Phi)$ in Equation (7) can be updated recursively. The updating procedure involves the following computation:

$$p(s_t = i|Y_t, x_t, \Phi) = \frac{p(s_t=i|Y_{t-1},x_{t-1},\Phi)p(y_t|s_t=i,Y_{t-1},x_t,\Phi)}{\sum_{i=1}^{S} p(s_t=i|Y_{t-1},x_{t-1},\Phi)p(Y_t|s_t=i,Y_{t-1},x_t,\Phi)} \tag{B1}$$

Denoting

$$\pi_{t,i} = p(s_t = i|Y_{t-1}, x_{t-1}, \Phi),\ i = 1, \dots S, \tag{B2}$$

and collecting $\pi_{t,i}$ in vector $\pi_t = (\pi_{t,1}, \pi_{t,2}, \dots, \pi_{t,S})$, Equation (7) can be written as

$$\pi_t = P\pi_{t-1} = P^2\pi_{t-2} = \cdots = P^t\pi_0 \tag{B3}$$

After a sufficient number of iterations a Markov chain reaches an ergodic distribution π^*, where the expected regime is independent from the initial condition, and which satisfies

$$\pi^* = P\pi^* \tag{B4}$$

B.2 Gibbs sampling

According to the Bayes rule, the posterior distribution of Φ conditional on the data is

$$p(\Phi \mid Y_T) \propto p(\Phi)p(Y_T \mid \Phi) \tag{B5}$$

The parameter matrix Φ is first partitioned into H blocks, $\Phi = (\Phi_1, \Phi_2, \dots, \Phi_\mathrm{H})$. Because of the analytical complexity of the posterior density $p(\Phi_1, \Phi_2, \dots, \Phi_\mathrm{H} \mid Y_T)$, there is no analytical solution to $p(\Phi_1, \Phi_2, \dots, \Phi_\mathrm{H} \mid Y_T)$, nor it is possible to simulate from its distribution. To this end, Sims and Zha (2004) suggest using the Gibbs sampler to obtain the joint density $p(\Phi_1, \Phi_2, \dots, \Phi_\mathrm{H}, S_T \mid Y_T)$. We assume that the conditional posterior densities $p(S_T \mid Y_T, \Phi_1, \Phi_2, \dots, \Phi_\mathrm{H})$, $p(\Phi_1 \mid Y_T, S_T, \Phi_2, \dots, \Phi_\mathrm{H})$, $p(\Phi_2 \mid Y_T, S_T, \Phi_1, \dots, \Phi_\mathrm{H})$, … , $p(\Phi_\mathrm{H} \mid Y_T, S_T, \Phi_1, \dots, \Phi_{\mathrm{H}-1})$ are known. Then the Gibbs sampler starts from arbitrary values for $\Phi^{(0)} = \left(\Phi_1^{(0)}, \Phi_2^{(0)}, \dots, \Phi_\mathrm{H}^{(0)}\right)$ that may be determined randomly, and samples alternatively from the density of each parameter block, conditional on the values of the other parameter blocks sampled in the previous iteration and the data. Thus, the following steps compose the algorithm for simulating draws from the posterior distribution of Φ (Waggoner and Zha 2003):

1. Choose the arbitrary values $\Phi^{(0)} = \left(\Phi_1^{(0)}, \Phi_2^{(0)}, \dots, \Phi_\mathrm{H}^{(0)}\right)$.

2. For $l = 1, \dots, L_1 + L_2$ and given $\Phi^{(l-1)} = \left(\Phi_1^{(l-1)}, \Phi_2^{(l-1)}, \dots, \Phi_\mathrm{H}^{(l-1)}\right)$, obtain $\Phi^{(l)} = \left(\Phi_1^{(l)}, \Phi_2^{(l)}, \dots, \Phi_\mathrm{H}^{(l)}\right)$ by

2.1. simulating $\Phi_1^{(l)}$ from the conditional density of $\Phi_1^{(l)}|\Phi_2^{(l-1)}, \Phi_3^{(l-1)}, \dots, \Phi_{\mathrm{H}}^{(l-1)}$,

2.2. simulating $\Phi_2^{(l)}$ from the conditional density of $\Phi_2^{(l)}|\Phi_1^{(l)}, \Phi_3^{(l-1)}, \dots, \Phi_{\mathrm{H}}^{(l-1)}$,

…

2.H simulating $\Phi_{\mathrm{H}}^{(l)}$ from the conditional density of $\Phi_{\mathrm{H}}^{(l)}|\Phi_1^{(l)}, \Phi_2^{(l)}, \dots, \Phi_{\mathrm{H}-1}^{(l-1)}$.

3. Collect the sequence $\Phi_1^{(0)}, \Phi_2^{(0)}, \dots, \Phi_{\mathrm{H}}^{(0)}, \dots, \Phi_1^{(L_1+L_2)}, \Phi_2^{(L_1+L_2)}, \dots, \Phi_{\mathrm{H}}^{(L_1+L_2)}$ and keep only the last values L_2 of the sequence.

Step 3 concerns a choice of L_1 and L_2. If the initial values $\Phi_1^{(0)}, \Phi_2^{(0)}, \dots, \Phi_{\mathrm{H}}^{(0)}$ are random but are not drawn from the target distribution, the first L_1 draws (the so-called "burn-in" period) are discarded. This is because (i) the first L_1 draws may not accurately represent the desired distribution and (ii) successive samples are not independent upon each other but rather form a Markov chain with some degree of correlation. By contrast, the second L_2 draws can be regarded as draws from the true posterior joint density. We set $L_1 = 5000$ and $L_2 = 25000$.

B.3 Priors

In the Gibbs sampler, we use the following priors. For the MSBVAR coefficients C_{s_t}, B_{s_t} and G_{s_t} we use flat priors. As suggested by Chib (1996), the prior of the transition matrix *P* is drawn from a Dirichlet distribution. For the k^{th} column of *P*, p_k, the prior density is given by $\pi(p_k) = \pi(p_{1k}, \dots, p_{Hk}) = \mathcal{D}(\alpha_{1k}, \dots, \alpha_{Hk}) \propto p_{1k}^{\alpha_{1k}-1} \cdot \dots \cdot p_{Hk}^{\alpha_{Hk}-1}$, where $\alpha_{hk} > 0$ for $h = 1, \dots, H$. We use hierarchical priors for variance and covariance matrix. The regime-invariant variance and covariance matrix is drawn from a Wishart distribution, $\Sigma \sim \mathcal{W}\left(\left[\sum_{s_t=i=1}^{S} \nu_{s_t} \left(\Sigma_{s_t}\right)^{-1}\right]^{-1}, \sum_{s_t=i=1}^{S} \nu_{s_t}\right)$, where the first element is a positive-definite $n \times n$ scale matrix and the second element is a prior degrees of freedom with $\nu_{s_t} = n + 2$. The regime-dependent variance and covariance matrix Σ_{s_t} is drawn from an inverse-Wishart distribution, $\Sigma_{s_t} \sim \mathcal{W}^{-1}\left(\left(\nu_{s_t}\Sigma\right)^{-1}, \nu_{s_t}\right)$.

B.4 Gibbs Sampler Diagnostics

We also undertake a diagnostic analysis that involves necessary checks if the generated posterior sample is drawn from a stationary distribution. Specifically, we evaluate the convergence of the MCMC simulation by means of the convergence diagnostic (CD) test statistic, proposed by Geweke (1992). This test statistic measures the equality of the means of the first and last part of a Markov chain. Consider the mean of $\bar{\theta} = 1/L \sum_{l=1}^{L} \theta_l$ of sequence of $l = 1, \dots, L$ draws of a certain parameter θ_l, where L denotes the size of the posterior sample. Following Koop (2003, Chapter 4), we divide the sequence L into three pieces, $l = 1, \dots, L_1$ (first piece), $l = L_1 + 1, \dots, L_2$ (second piece) and $l = L_2 + 1, \dots, L$ (third piece), and we discard the second piece. [21]

If the samples are drawn from a stationary distribution, then the means calculated from the first ($\bar{\theta}_1$) and third ($\bar{\theta}_3$) segments should not be statistically different, and the corresponding test statistic has an asymptotically standard normal distribution:

$$CD = \frac{\bar{\theta}_1 - \bar{\theta}_3}{\sqrt{nse_1^2 + nse_3^2}} \xrightarrow{d} N(0,1), \tag{B6}$$

where nse_1^2 and nse_3^2 are the numerical standard errors squared. [22] We calculate the test statistic for all the parameters of the model. Our samples have passed the convergence (at the 5% significance level) for nearly all parameters. [23] Results of the CD test are summarized in Table 6.

– Please Insert Table 6 about here –

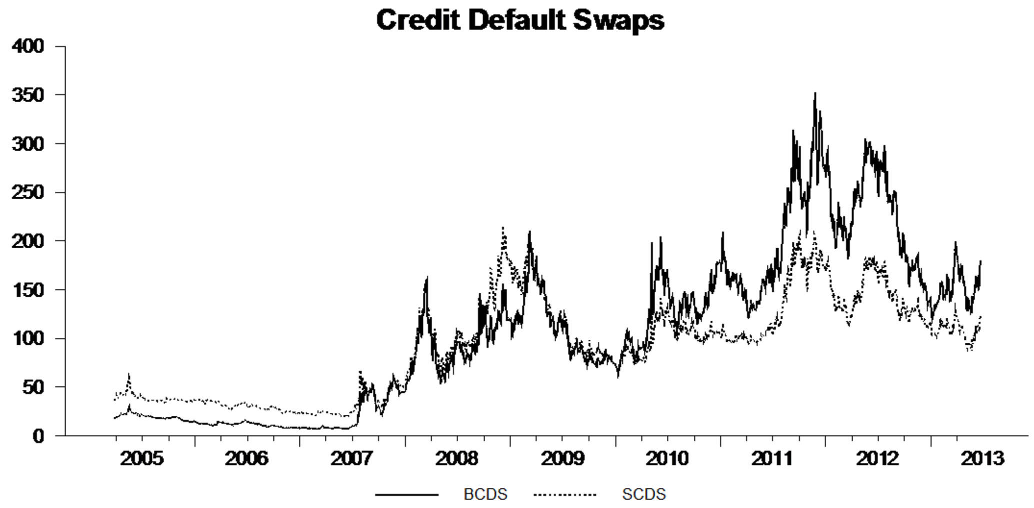
[21] According to Koop (2003, Chapter 4), the size of the first and third pieces is constrained by $L_1/L = 0.1$ and $(L - L_2)L = 0.6$, respectively.

[22] The Gibbs sampler can be used to estimate the mean of a generic function $g(\theta_l)$. Geweke's method builds upon the assumption that the nature of the MCMC process and the function $g(\theta_l)$ imply the existence of a spectral density $S_g(\omega)$ for L draws of the function g with no discontinuities at frequency 0 (Cowles and Carlin 1996). Then, for the estimator of $E[g(\theta_l)]$, $\bar{g}_L$, the asymptotic variance is $S_g(0)/L$, referred by Geweke to as the numerical standard error squared, nse^2.

[23] The mean absolute value of the CD statistic is 0.8354 (at 5% significance level, the critical value is ±1.96), and there are only 6 parameters (out if 123) that do not pass the convergence test.

Figures

Panel A



Panel B

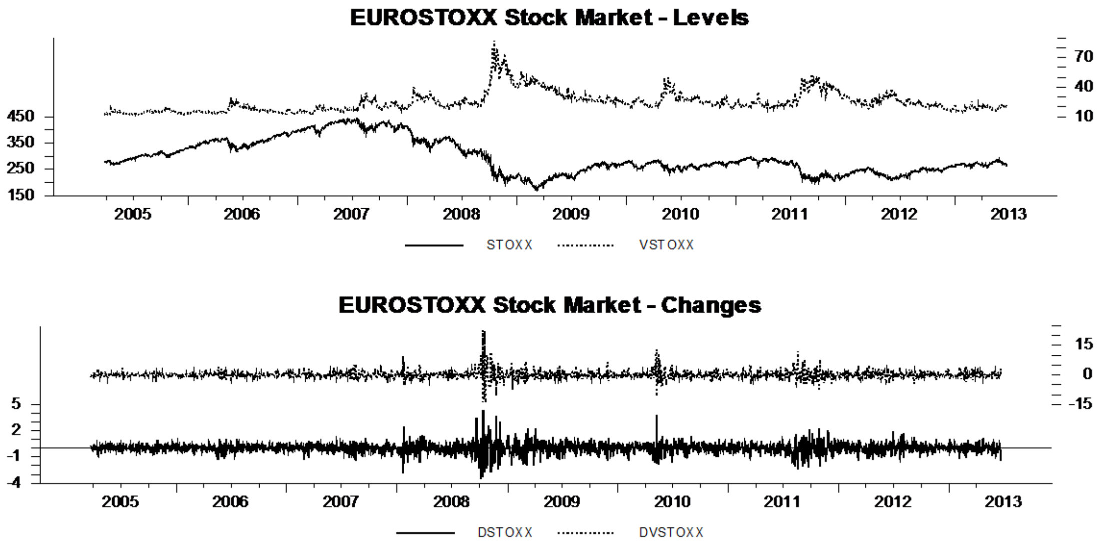
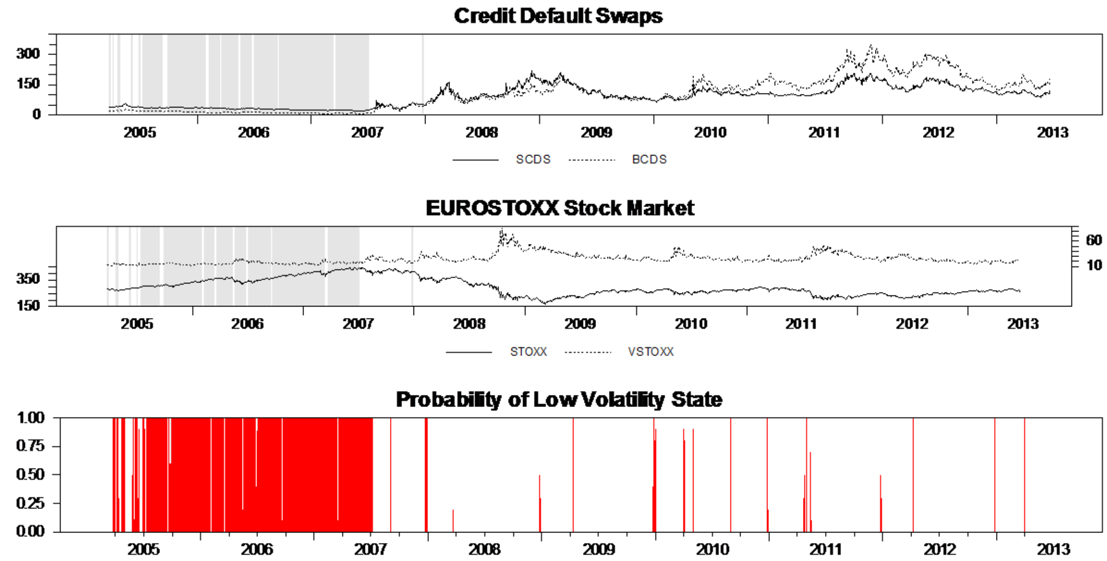


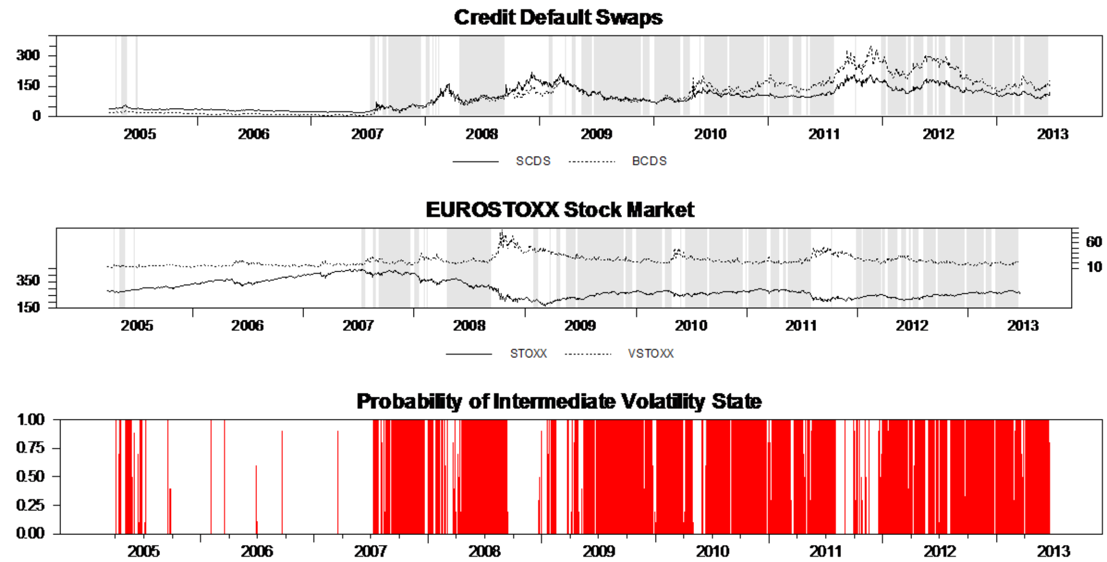
Figure 1. Developments in Credit Default Swap and Stock Markets

Notes: Figure 1 depicts variation over time in the CDS market (Panel A) and in the stock market (Panel B). Panel B shows variation over time in levels (upper graph) and in changes (lower graph). The EUROSTOXX stock market index is on the left scale, and the VSTOXX volatility index is on the right scale.

Panel A



Panel B



Panel C

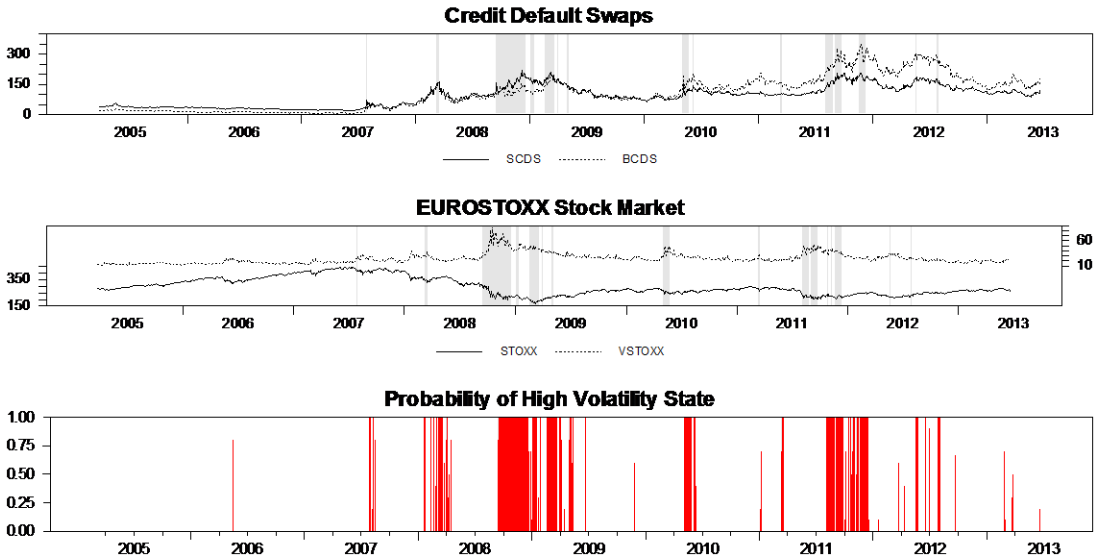
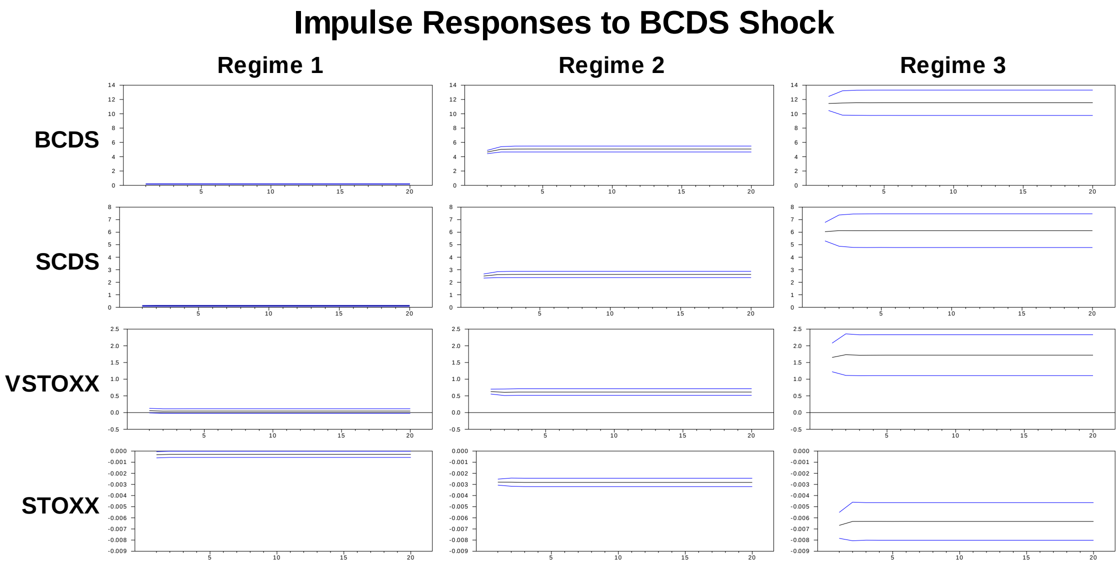


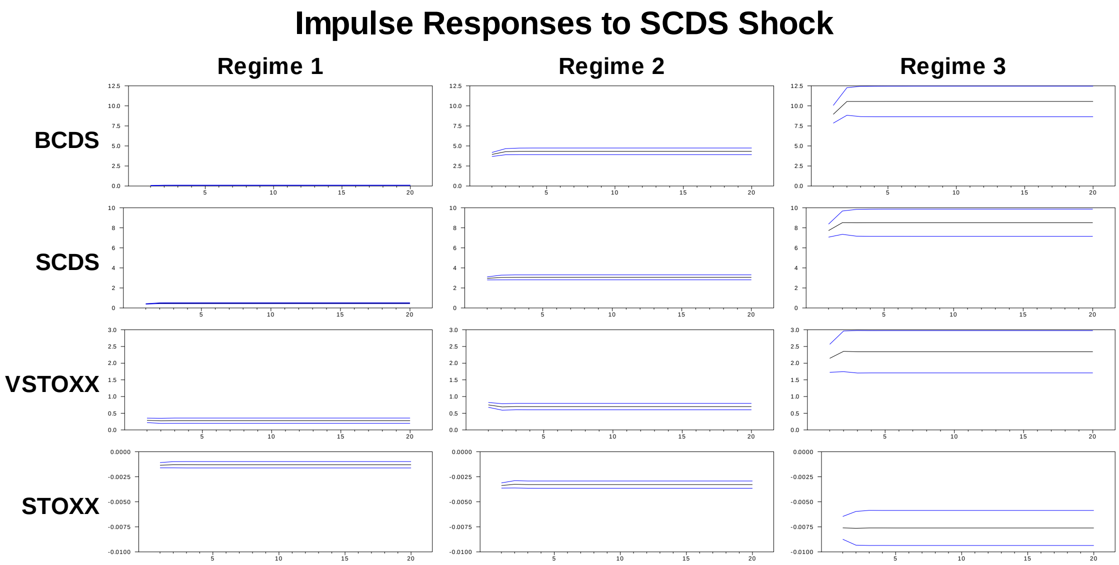
Figure 2. Regimes in the Credit Default Swap Market

Notes: Figure 2 identifies the Markov regimes (states), estimated using the MSBVAR model. Panel A depicts the low volatility regime. Panel B depicts the intermediate volatility regime. Panel C depicts the high volatility regime. Figure 2 also shows the developments in the CDS and stock markets during the three regimes. Regime probabilities are given by the smoothed estimates (in solid red line). A regime is defined as a region (or polygon) with the highest smoothed probability, i.e., $s_t = i^* = arg\,\max_i p(s_t = i|Y_T, X_T, \Phi)$ (grey polygon). Regime 1 prevailed from the beginning of the sample (March 2005) till July 2007. In July 2007, the CDS market switched from regime 1 to regime 2. Regime 2 dominated the remainder of the sample and was only occasionally interrupted by regime 3, when the BCDS and SCDS spreads showed an accelerated increase and decrease with a turning point in the middle.

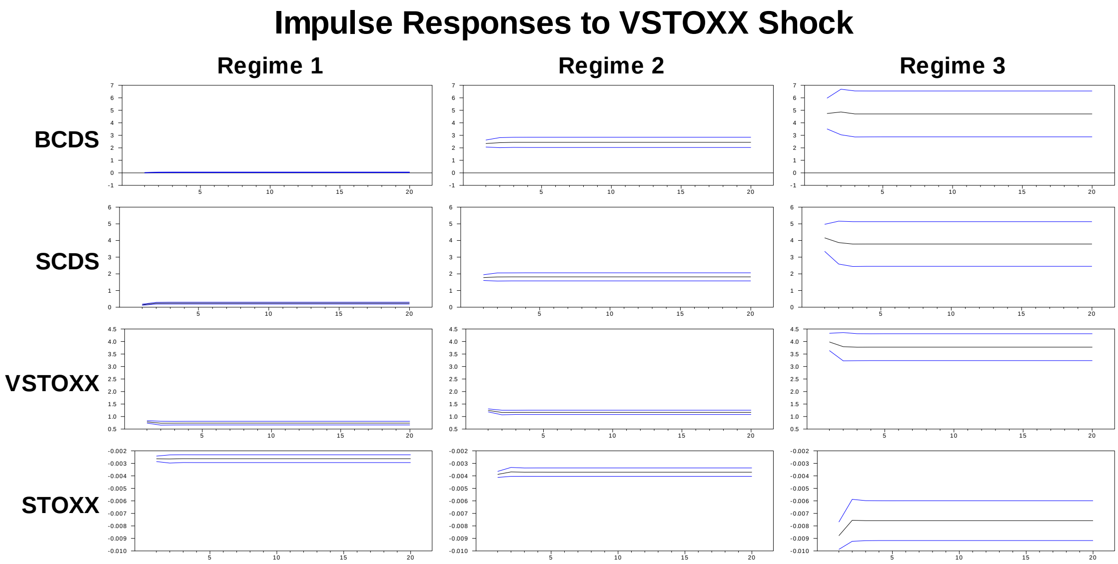
Panel A



Panel B



Panel C



Panel D

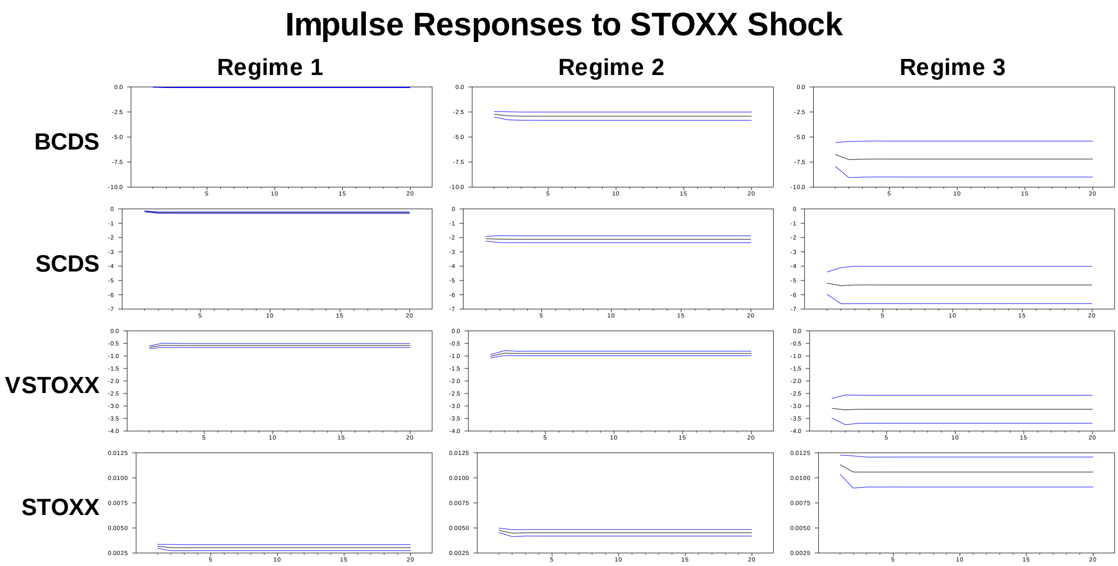


Figure 3. Regime-Dependent Impulse Response Functions

Notes: This figure depicts the generalized impulse response functions of the endogenous variables of the MSBVAR in the low volatility, intermediate volatility and high volatility regimes (Regimes 1, 2 and 3, respectively). Panel A summarizes responses to a shock to BCDS spread. Panel B summarizes responses to SCDS spread. Panel C summarizes responses to a shock to VSTOXX volatility index. Panel D summarizes responses to a shock to EUROSTOXX stock market index. Confidence intervals show 2 standard deviations from the impulse responses.

Tables

Table 1 – Summary Statistics

Panel A. Variables in levels

Variables	Obs	Mean	Median	Max	Min	Std	Skew	Kurt	JB	Prob
BCDS	2154	106.8703	101.3290	353.0000	7.0000	81.9862	0.5518	2.5016	131.5949	0.0000
SCDS	2154	91.7861	97.0300	215.9170	20.0940	49.5823	0.2272	2.0670	96.6516	0.0000
VSTOXX	2154	24.7843	22.575	87.51	11.720	10.176	1.7307	7.2344	2684.62	0.0000
STOXX	2154	296.161	276.90	442.9	169.39	64.489	0.5963	2.3358	167.2398	0.0000
IRS_1	2154	2.2545	1.7735	5.4790	0.1280	1.5541	0.4263	1.7779	199.2768	0.0000
IRS_2	2154	2.4926	2.1700	5.5130	0.3090	1.3919	0.2957	1.8584	148.3588	0.0000
IRS_3	2154	2.6351	2.4090	5.4450	0.4020	1.3142	0.1369	1.9218	111.0691	0.0000
IRS_4	2154	2.7796	2.6290	5.3610	0.5530	1.2373	0.0020	2.0013	89.5122	0.0000
IRS_5	2154	2.9166	2.8300	5.2810	0.7230	1.1627	-0.1050	2.0812	79.7167	0.0000
IRS_6	2154	3.0423	3.0125	5.2130	0.8880	1.0966	-0.1918	2.1502	78.0304	0.0000
IRS_7	2154	3.1545	3.1665	5.1650	1.0480	1.0415	-0.2608	2.2033	81.3919	0.0000
IRS_8	2154	3.2530	3.2945	5.1390	1.2000	0.9969	-0.3118	2.2377	87.0514	0.0000
IRS_9	2154	3.3397	3.3960	5.1260	1.3420	0.9612	-0.3492	2.2579	93.1922	0.0000
IRS_10	2154	3.4173	3.4875	5.1210	1.4670	0.9316	-0.3786	2.2721	99.0034	0.0000
IRS_12	2154	3.5496	3.6460	5.1330	1.6790	0.8850	-0.4275	2.2968	109.9771	0.0000
IRS_15	2154	3.6832	3.8150	5.1410	1.8310	0.8443	-0.4794	2.3053	125.8313	0.0000
IRS_20	2154	3.7614	3.9125	5.1150	1.8430	0.8284	-0.5225	2.2783	144.7544	0.0000
IRS_25	2154	3.7473	3.8925	5.0850	1.8130	0.8265	-0.4750	2.1892	139.9947	0.0000
IRS_30	2154	3.7082	3.8485	5.0690	1.7760	0.8281	-0.4024	2.0810	133.9404	0.0000

Panel B. Variables in first differences										
Variables	Obs	Mean	Median	Max	Min	Std	Skew	Kurt	JB	Prob
BCDS	2154	0.0752	0.0000	52.4410	-63.1400	6.0316	-0.3859	17.0517	17775.6	0.0000
SCDS	2154	0.0403	0.0000	22.8400	-39.4700	3.9713	-0.3527	12.8779	8801.83	0.0000
VSTOXX	2154	0.0049	-0.0650	22.6400	-13.9800	1.9308	1.7316	27.5295	55078.9	0.0000
STOXX	2154	-0.0032	0.0210	9.9621	-8.2498	1.4179	-0.0517	8.8382	3060.06	0.0000
IRS_1	2154	-0.0010	0.0000	0.2860	-0.2150	0.0333	0.0892	13.5738	10037.4	0.0000
IRS_2	2154	-0.0010	0.0000	0.3280	-0.2820	0.0415	0.1286	8.8275	3053.84	0.0000
IRS_3	2154	-0.0010	0.0000	0.2910	-0.2950	0.0441	0.0841	7.2539	1626.62	0.0000
IRS_4	2154	-0.0010	0.0000	0.2290	-0.2640	0.0438	0.0602	5.9112	761.943	0.0000
IRS_5	2154	-0.0009	0.0000	0.2450	-0.2350	0.0437	0.0506	5.1904	431.506	0.0000
IRS_6	2154	-0.0009	0.0000	0.2770	-0.2040	0.0431	0.0726	5.1932	433.600	0.0000
IRS_7	2154	-0.0009	0.0000	0.3090	-0.1750	0.0428	0.1043	5.6372	628.111	0.0000
IRS_8	2154	-0.0009	0.0000	0.3330	-0.1880	0.0428	0.1184	6.2777	969.232	0.0000
IRS_9	2154	-0.0009	0.0000	0.3570	-0.2120	0.0430	0.1367	7.0433	1473.95	0.0000
IRS_10	2154	-0.0009	0.0000	0.3790	-0.2350	0.0434	0.1450	7.8730	2138.80	0.0000
IRS_12	2154	-0.0008	0.0000	0.4390	-0.2970	0.0443	0.2401	10.5165	5091.32	0.0000
IRS_15	2154	-0.0008	0.0000	0.5060	-0.3560	0.0460	0.3823	14.4166	11750.3	0.0000
IRS_20	2154	-0.0008	0.0000	0.5610	-0.3620	0.0485	0.5185	17.2527	18328.2	0.0000
IRS_25	2154	-0.0008	0.0000	0.5960	-0.3440	0.0502	0.5622	18.7527	22384.7	0.0000
IRS_30	2154	-0.0008	0.0000	0.6320	-0.3460	0.0522	0.5681	20.2324	26767.5	0.0000

Notes: This table summarizes descriptive statistics (sample mean, median, maximum, minimum, standard deviation, skewness, excess kurtosis, the Jarque-Bera test statistic, and the p-value associated to the Jarque-Bera test statistic) of the European banks' credit default swap spread (BCDS, measured in basis points), the European sovereign credit default swap spread (SCDS, measured in basis points), the VSTOXX volatility index (VSTOXX, measured in index points), the EUROSTOXX stock index (STOXX, measured in percentage points), and the fixed-for-floating interest rate swaps ("you pay me a floating 3-month LIBOR interest rate, I pay you a fixed interest rate") for maturities from 1 to 30 years (IRS_M, where "_M" denotes maturity, measured in annualized percentage points). The interest rate swaps are used to compute the first ("level") and the second ("slope") principal components. Panel A summarizes descriptive statistics of the aforementioned variables measured in levels. Panel B summarizes descriptive statistics of the variables in first differences (STOXX is measured in percentage change). The sample period is 22/03/2005 – 21/06/2013 that contains a total of 2154 daily observations.

Table 2 – Unit Root Tests

VARIABLES	OBS	ADF TEST		KPSS TEST		PP TEST		ZA TEST			
		CONST	TREND	CONST	TREND	CONST	TREND	CONST	BREAK	TREND	BREAK
BCDS	2154	-1.6233	-2.9923	28.476*	1.1049*	-1.7481	-3.2981	-3.1318	2010/04/14	-5.1498*	2011/07/27
SCDS	2154	-1.8319	-2.4593	21.738*	1.9238*	-1.9375	-2.6790	-3.4945	2008/01/02	-3.4844	2007/10/16
VSTOXX	2154	-3.3764*	-3.4380*	6.6455*	3.2586*	-3.9574*	-4.0875*	-4.3282	2007/12/27	-5.1131*	2008/09/03
STOXX	2154	-1.1942	-1.9697	17.524*	2.5179*	-1.2585	-2.0443	-4.1126	2008/05/20	-3.8712	2008/01/02
IRS_1	2154	0.0546	-1.6708	22.886*	3.6751*	0.1508	-1.6980	-6.3002*	2008/09/26	-8.4582*	2008/09/26
IRS_2	2154	-0.1083	-1.7228	23.717*	3.9587*	-0.0829	-1.7415	-4.4253	2008/09/26	-5.9085*	2008/09/26
IRS_3	2154	-0.1968	-1.7666	24.479*	4.3434*	-0.1933	-1.7916	-3.6160	2008/09/26	-5.0162	2008/09/26
IRS_4	2154	-0.2338	-1.7734	24.645*	4.6910*	-0.2361	-1.7973	-3.1363	2008/09/26	-4.4963	2008/09/26
IRS_5	2154	-0.2711	-1.7700	24.551*	4.9764*	-0.2800	-1.7929	-2.8091	2008/09/26	-4.1967	2008/09/26
IRS_6	2154	-0.3032	-1.7662	24.396*	5.2328*	-0.3118	-1.7867	-2.5628	2008/09/26	-4.0304	2008/09/26
IRS_7	2154	-0.3419	-1.7679	24.249*	5.4532*	-0.3495	-1.7862	-2.4693	2011/05/06	-3.9600	2008/09/26
IRS_8	2154	-0.3866	-1.7766	24.126*	5.6319*	-0.3969	-1.7959	-2.5539	2006/12/05	-3.9560	2008/09/25
IRS_9	2154	-0.4369	-1.7893	24.018*	5.7744*	-0.4519	-1.8119	-2.6946	2006/12/05	-3.9870	2008/09/25
IRS_10	2154	-0.4865	-1.8053	23.883*	5.8928*	-0.5084	-1.8323	-2.8156	2006/12/05	-4.0257	2008/09/25
IRS_12	2154	-0.5773	-1.8376	23.518*	6.0721*	-0.6090	-1.8743	-3.0184	2006/12/05	-4.0943	2008/09/25
IRS_15	2154	-0.6945	-1.8985	23.183*	6.1974*	-0.7339	-1.9438	-3.2193	2006/12/05	-4.1665	2007/03/22
IRS_20	2154	-0.8193	-2.0098	23.654*	6.1367*	-0.8636	-2.0639	-3.3791	2006/12/07	-4.2255	2007/03/22
IRS_25	2154	-0.9605	-2.1798	24.577*	5.6992*	-0.9834	-2.2151	-3.4893	2006/12/07	-4.3690	2008/09/24
IRS_30	2154	-1.0914	-2.3495	25.378*	5.2379*	-1.0979	-2.3686	-3.5871	2006/12/07	-4.6317	2008/09/24
SLOPE	2154	-1.1993	-1.8883	15.677*	3.1574*	-3.4145	-1.8959	-6.1667*	2008/10/02	-6.0387*	2008/10/02

Notes: This table summarizes results of the Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), Phillips-Perron (PP) and Zivot-Andrews (ZA) tests for a unit root. Under the ADF, PP and ZA tests, the null hypothesis is that the series features a unit root. Under the KPSS test, the null is that the series is stationary. The ADF (KPSS and PP) test equations comprise a constant (CONST) and both a constant and a trend (TREND), the 5% critical values being -2.8634 and -3.4145 (0.4630 and 0.1460, -2.8634 and -3.4145), respectively. The 5% critical values for the ZA test are -4.8000 and -5.0800 under the assumption of a break in the constant (CONST) and in both the constant and the trend (TREND), respectively. The ZA test comprises a constant and a trend, while allowing for a single break in the constant (CONST) and in both the constant and the trend (TREND). The ZA test also provides the estimated break date (BREAK). Asterisk (*) indicates coefficients significant at the 5% or higher level of significance. The sample period is 22/03/2005 – 21/06/2013 that contains a total of 2154 daily observations.

Table 3 – Coefficients Of Correlation

Variables	BCDS	SCDS	VSTOXX	STOXX
BCDS	1.0000	0.8227	0.4730	-0.5944
SCDS	0.8227	1.0000	0.5860	-0.6898
VSTOXX	0.4730	0.5860	1.0000	-0.7978
STOXX	-0.5944	-0.6898	-0.7978	1.0000
IRS_1	-0.1263	-0.1623	-0.1660	0.1382
IRS_2	-0.1987	-0.2444	-0.2059	0.2114
IRS_3	-0.2242	-0.2671	-0.2234	0.2370
IRS_4	-0.2395	-0.2741	-0.2251	0.2460
IRS_5	-0.2510	-0.2789	-0.2255	0.2517
IRS_6	-0.2602	-0.2799	-0.2255	0.2530
IRS_7	-0.2698	-0.2808	-0.2255	0.2529
IRS_8	-0.2755	-0.2791	-0.2241	0.2511
IRS_9	-0.2787	-0.2765	-0.2223	0.2482
IRS_10	-0.2806	-0.2740	-0.2201	0.2449
IRS_12	-0.2820	-0.2710	-0.2171	0.2373
IRS_15	-0.2805	-0.2666	-0.2159	0.2286
IRS_20	-0.2724	-0.2576	-0.2145	0.2190
IRS_25	-0.2687	-0.2539	-0.2113	0.2133
IRS_30	-0.2651	-0.2502	-0.2083	0.2088

Notes: This table summarizes the Pearson coefficients among the dependent and exogenous variables. All variables are in first difference (EUROSTOXX stock market index is in percentage change). The sample period is 22/03/2005 – 21/06/2013 that contains a total of 2154 daily observations.

Table 4 – Marginal Log-Likelihoods

Variables	Regimes (cols), Methods (rows)	1	2	3	4
BCDS	BS	-959.37	-928.41	**-904.80**	-912.55
	Chib	-959.11	-927.98	**-903.51**	-910.02
SCDS	BS	-984.70	-971.56	**-953.39**	-959.67
	Chib	-984.52	-971.07	**-952.44**	-957.29
STOXX	BS	-989.32	-981.24	**-972.99**	-975.92
	Chib	-989.10	-980.65	**-972.13**	-973.21
VSTOXX	BS	-884.09	-879.53	**-862.44**	-866.63
	Chib	-883.86	-878.97	**-861.80**	-864.07

Notes: This table summarizes the marginal log-likelihood values for bridge sampling (Meng and Wong 1996) and Chib's (1995) methods that are used to select among various models differing in the number of Markov regimes. The number of regimes is given in columns. The highest marginal log-likelihood value is highlighted in bold. The sample period is 22/03/2005 – 21/06/2013 that contains a total of 2154 daily observations.

Table 5 – Estimation Results

State	Low Volatility				Middle Volatility				High Volatility			
Panel A. Coefficient estimates of exogenous variables (LEVEL = PC1, SLOPE = PC2)												
Equations (cols), predictors (rows)	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX
$\mathrm{LEVEL_t}$	-0.004308	-0.022335*	-0.035510*	0.000180*	-0.410049*	-0.289575*	-0.105170*	0.000394*	-0.695845*	-0.476360*	-0.208583*	0.000629*
	(0.003128)	(0.006608)	(0.012840)	(0.000051)	(0.044823)	(0.028660)	(0.011928)	(0.000046)	(0.122142)	(0.082758)	(0.042201)	(0.000121)
$\mathrm{SLOPE_t}$	-0.001674	0.075234*	0.118808	-0.000394*	-0.292984*	-0.121761	-0.060787*	0.000165	-0.197803	0.330842	0.215780	-0.000497
	(0.011769)	(0.026392)	(0.050906)	(0.000202)	(0.109188)	(0.070261)	(0.028938)	(0.000110)	(0.342764)	(0.233730)	(0.120466)	(0.000342)
Panel B. Coefficient estimates of the variance and covariance matrix												
Variances and covariances	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX
BCDS	0.033311*				21.709597*				131.08600*			
	(0.002406)				(1.071273)				(11.25193)			
SCDS	0.020444*	0.163789*			11.632908*	8.729875*			69.228344*	59.745025*		
	(0.003767)	(0.010921)			(0.623586)	(0.442355)			(6.629798)	(5.041232)		
VSTOXX	0.010471*	0.116196*	0.621180*		2.926746*	2.217390*	1.559256*		18.921706*	16.600610*	15.892555*	
	(0.006337)	(0.014912)	(0.037731)		(0.212338)	(0.142085)	(0.073835)		(2.826224)	(2.035725)	(1.380067)	
STOXX	-0.000062*	-0.000546*	-0.002081*	0.000010*	-0.013011*	-0.009970*	-0.004851*	0.000023*	-0.076489*	-0.058801*	-0.035053*	0.000128*
	(0.000026)	(0.000061)	(0.000139)	(0.000001)	(0.000834)	(0.000562)	(0.000246)	(0.000001)	(0.008741)	(0.006149)	(0.003412)	(0.000011)
Panel C. Estimated transition probabilities												
Low	0.917195* (0.013353)				0.035457* (0.006491)				0.016572* (0.008218)			
Middle	0.065859* (0.012212)				0.921021* (0.009767)				0.174433* (0.028154)			
High	0.016946* (0.006041)				0.043522* (0.007692)				0.808994* (0.028543)			
Panel D. Coefficient estimates of exogenous variables (LEVEL = IRS_5, SLOPE = IRS_10-IRS_2)												
Equations (cols), predictors (rows)	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX
$\mathrm{LEVEL_t}$	-0.271198	-1.887857*	-3.328470*	0.016621*	-26.55779*	-20.11069*	-7.147764*	0.027714*	-66.62242*	-46.71224*	-19.25354*	0.062165*
	(0.238971)	(0.520544)	(1.016210)	(0.004038)	(3.486721)	(2.234848)	(0.927679)	(0.003540)	(10.90962)	(7.257398)	(3.750212)	(0.010695)
$\mathrm{SLOPE_t}$	0.010473	0.044699	0.013698	0.000013	-0.262120	-0.382652*	-0.065110	0.000583*	0.497042	0.153603	-0.332376	0.001056
	(0.020078)	(0.044886)	(0.085252)	(0.000339)	(0.228710)	(0.147776)	(0.061742)	(0.000234)	(1.270638)	(0.854366)	(0.439728)	(0.001252)

Notes: Panel A summarizes the estimated effects of the exogenous variables in the MSBVAR model. Credit default swaps and the volatility index are in first differences, and the stock market index is in first log-difference. In Panel A, LEVEL and SLOPE are the principal components on interest rate swaps in first differences. Panel B summarizes the estimated residual variance and covariance matrix. Panel C summarizes the estimated transition probabilities. The elements of the transition probabilities matrix are indexed according to $P = \begin{pmatrix} p_{11} & \cdots & p_{1m} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mm} \end{pmatrix}$, where $p_{ij} = Pr(s_{t+1} = j | s_t = i)$ and $\sum_{j=1}^{m} p_{ij} = 1$ for all $i = 1, \dots, m$. In Panel D, LEVEL and SLOPE are the 5-year interest rate swap, and the difference between 10-year and 2-year interest rate swaps. The estimated coefficient standard errors are provided in parentheses. Asterisk (*) indicates coefficients significant at the 5% or higher level of significance.

Table 6 – Geweke's Test for Convergence Diagnostics for the MSBVAR Model

Panel A. Coefficient estimates of the conditional mean

State	Low Volatility				Middle Volatility				High Volatility			
Equations (in columns), predictors (in rows)	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX
CONST	1.588078	-0.121388	0.302845	-0.854201	0.195473	0.474492	-0.205195	-0.123615	-1.354168	-1.098942	-0.467640	0.116741
$BCDS_{t-1}$	-0.514662	-1.949985	0.615100	-1.164118	-2.122899	-2.030775	1.230305	0.848046	-0.437183	1.065941	-0.107624	0.346869
$SCDS_{t-1}$	1.898519	1.913460	0.555688	-0.356732	0.695109	1.508835	-1.102344	-0.094037	1.557627	-0.287325	-0.271169	-0.681326
$VSTOXX_{t-1}$	-1.340192	0.444608	0.687256	-1.528116	0.142531	0.308209	0.981044	-0.909770	0.169732	1.282236	1.176771	-1.390332
$STOXX_{t-1}$	0.579263	1.208924	1.412226	-1.576613	-0.337105	0.180561	0.484668	-0.144377	0.844522	1.064957	0.649835	-1.122415
$LEVEL_t$	1.108024	1.690854	0.111352	0.357669	0.627888	0.257798	0.120193	-0.764057	-2.435228	-2.141314	-1.082070	2.050298
$SLOPE_t$	-0.564224	1.492036	-0.434030	-0.688725	0.973561	0.464250	0.109763	-0.746655	2.401704	1.574654	0.858717	-1.912174

Panel B. Coefficient estimates of the variance and covariance matrix

State	Low Volatility				Middle Volatility				High Volatility			
Variances and Covariances	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX	BCDS	SCDS	VSTOXX	STOXX
BCDS	-0.181310				0.391166				-0.870456			
SCDS	-1.290606	0.336606			1.178840	1.328869			-0.132640	0.096560		
VSTOXX	-1.733400	-0.236674	-0.278135		0.454771	0.389028	-0.242417		-0.360529	0.545722	1.257695	
STOXX	1.651653	-0.139180	0.322103	0.002634	-0.753034	-0.577163	0.105807	0.020016	-0.021434	-1.017541	-1.758634	1.618755

Panel C. Estimated Transition probabilities

	Low Volatility	Middle Volatility	High Volatility
Low	0.967370	-1.912020	-0.519759
Middle	-0.722722	0.942298	0.845139
High	-1.093754	0.503790	-0.765985

Notes: This table summarizes results of the convergence diagnostic test, proposed by Geweke (1992). The null hypothesis asserts that the coefficient is not statistically different in the first and in the third run of a Markov chain. Critical values are drawn from a standard normal distribution. Asterisk (*) indicates coefficients significant at the 5% or higher level of significance.