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The Role of a Changing Market Environment for Credit Default Swap Pricing

by Julian S. Leppin and Stefan Reitz

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Kiel Institute for the World Economy, Hindenburgufer 66, 24105 Kiel, Germany

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JEL-Code: G13, G15, C33
Keywords: CDS spreads, Financial Crisis, Panel Smooth Transition

Stefan Reitz
Kiel University
Institute for Quantitative Business and Economic Research
24098 Kiel, Germany

Kiel Institute for the World Economy
24000 Kiel
Email: Stefan.reitz@ifw-kiel.de

Julian S. Leppin
Hamburg Institute of International Economics
24148 Hamburg, Germany
Email: leppin@hwwi.org

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Julian S. Leppin* Stefan Reitz†

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Abstract

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*University of Kiel and Hamburg Institute of International Economics (HWWI), Heimhuder Strasse 71, 20148 Hamburg, Germany; Email: leppin@hwwi.org.

†Kiel Institute for the World Economy, Germany, and Institute for Quantitative Business and Economics Research, University of Kiel.

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1 Introduction

Triggered by the money market breakdown in the aftermath of the Lehman default in 2008 the European Central Bank (ECB) launched a number of measures to ensure firms' access to credit. However, the ECB's unconventional monetary policy via the credit channel exerted little influence on bank lending volume to the real sector of the economy (di Patti and Sette, 2012; Blot and Labondance, 2013). Besides liquidity hoarding, balance sheet considerations and deleveraging, this is due to the fact that elevated credit risk of banks' counterparts clearly dominates lending rates in times of crisis. Against this backdrop it is important to understand the time-varying influence of credit risks' driving forces. One of the most popular measures of the credit component of lending rates are credit default swaps (CDS).[1] CDS are insurance contracts ensuring the protection buyer the par value of the underlying bond if the firm defaults or restructure its debts. In return, the protection seller receives a periodic payment (the CDS spread) expressed in percentage points of the bond's par value.[2] CDS became increasingly popular in the early 2000s when their notional outstanding volume rose quickly peaking in 2007 at \$60 trillion. Thereafter, traded volumes considerably declined to \$30 trillion in the first half of 2010 (Vause, 2010) and further in December 2013, when the notional outstanding amount was \$21 trillion according to the Bank of International Settlements (BIS). Although declining over time the overall high liquidity in the market ensures a fast adaption to changing market circumstances, which renders the CDS market especially appealing to study the determinants of credit risks. Following the Merton (1974) model the literature mainly reported empirical evidence on the linear influence of the risk-free rate, the firm value, its debt level, and the asset volatility. However, the unconditional estimates of parameter coefficients represent sample-specific averages and do not account for a time-varying market environment. This is particularly relevant during times of crisis when agents' perceptions of risk undergo massive changes.

Thus, the aim of the paper is to investigate the impact of a changing market environment on the relationship between CDS spreads written on debt from EURO STOXX 50 firms and their standard fundamentals. A Panel Smooth Transition Regression (PSTR) is applied to estimate the time-varying coefficients of the pricing model. The sample includes data from 2004 to 2013 thereby considering the financial crisis with extensive changes in

[1] Another possibility to analyze credit risk is the use of bond spreads however they suffer from the need to identify a risk-free bond as a benchmark. Furthermore, the bond market is less liquid which results in illiquidity premia for bond prices (Longstaff et al., 2005) and changes in the underlying credit risk are incorporated quicker in the CDS market than in the bond market (Blanco et al., 2005; Zhu, 2006).

[2] One of the main differences to an insurance contract is the missing obligation to hold the underlying bond. An exception are European government bonds for which naked CDS are forbidden since November 2012.

the pricing of credit default swaps. From a technical perspective, market conditions determine the flexible transition between the two or more different regimes of CDS pricing and are approximated by a set of variables such as the ECB's systemic stress composite index, the Sentix index for current and future economic situation, and the VStoxx. The estimation of a multivariate transition function including the selection of the appropriate transition variables and the identification of the required weights is performed on the basis of Lof (2012). Extending the (multivariate) panel smooth transition regression model we allow for heterogeneous transition functions implying that different pricing variables are allowed to interact with different transition variables. This greatly increases the flexibility of the model since we do not impose the restriction of a "one-fits-all" transition function for different pricing variables.

The remainder of this study is structured as follows. Section 2 reviews the related literature. Section 3 presents the panel smooth transition regression model with the considered generalizations. Section 4 describes the data and the theoretical pricing models for CDS spreads. Section 5 presents the result from the estimation and Section 6 concludes.

2 Literature

In fact, the favorable characteristics of the CDS market attracted a lot of research in the field. One of the first works is from Skinner and Townend (2002), they tests for potential determinants of CDS spreads derived from the option pricing theory. The risk-free rate, the yield of the underlying asset and volatility turned out to be the most important drivers. Of particular interest in the literature is the relation between CDS spreads and bond yield spreads (e.g. Longstaff et al., 2005; Hull et al., 2004; Blanco et al., 2005; Zhu, 2006) since different prices for credit risks would lead to arbitrage possibilities. Longstaff et al. (2005) examine the differences in the spreads from CDS and bond yields, they conclude that illiquidity is an important determinant. Hull et al. (2004) and Houweling and Vorst (2005) use the the relation between bond yield spreads and CDS spreads to identify the correct risk-free interest rate. The influence of volatility is a further topic in the literature. Ericsson et al. (2009) and Zhang et al. (2009) show the high importance of firm-specific historical volatility while Cao et al. (2010) document the superior performance of option-implied volatility compared with historical volatility. Wang et al. (2013) examine the influence of the variance risk premia, defined as the difference between the model-free option-implied variance and the expected variance based on the realized volatility. Furthermore, the financial crisis brought up the issue of counterparty risk. For CDS spreads the presence of counterparty risk in CDS pricing is documented by Arora et al. (2012), however, they found only a small magnitude.

Recent studies have increasingly used regime switching and nonlinear models to explain the changing determinant of CDS spreads. Alexander and Kaeck (2008) use a Markov switching model to determine regime dependent influences on iTraxx indices (index of the most liquid single CDS). They find pronounced differences between the regimes for the period from June 2004 until June 2007. Especially, they find improved explanatory power of structural variables in the volatile regime. Chan and Marsden (2014) resort to Markov switching models as well. They use a prolonged period (2003-2011) which includes the financial crisis. Using a broad range of macroeconomic determinants, they confirm the need to consider regime changes when analyzing CDS spreads. Estimated betas tend to be higher during what is described as the volatile regime. This highlights a drawback of the Markov model. Even though Markov switching models are well suited to identify different regimes, they are unable to identify the underlying variables driving the transition. This could be overcome by the use of panel smooth transition regression (PSTR) models. The model was introduced by González et al. (2005) and allows to test and estimate potential nonlinear determinants of CDS spreads. Most smooth transition regression models use univariate transition functions, characterized by a single transition variable, only few multivariate application of smooth transition are available and all are restricted to time series estimators. Lof (2012) uses a smooth transition autoregressive model to identify the changing fractions of chartists and fundamentalists in the pricing of assets. In the multivariate setup, up to three different macroeconomic variables are used jointly in the transition function to explain switches from chartists to fundamentalists and vice versa. Times of positive macroeconomic news are characterized by greater fractions of chartists while fundamentalists dominate during downturns. Related approaches with multivariate transition functions can be found in Medeiros and Veiga (2005) and Becker and Osborn (2012) where transition is driven by different lags of the endogenous variable. Multivariate transition functions for threshold models are considered by Massacci (2013).

3 The Model

In general, two theoretical frameworks are commonly used to model CDS spreads, the structural approach based on the work from Merton (1974) and the reduced-form approach as outlined e.g. in Duffie and Singleton (2003). The reduced-form approach assumes that default is caused by a random jump process, available market data are used to calibrate the model. The advantage of the reduced-form approach is the superior empirical performance compared to the structural approach,[3] however, it suffers from the lack of

[3]Evidence of the bad empirical performance of structural models can be found in Eom et al. (2004), amongst others.

theoretic foundation which is given for structural models. In the Merton model the value of the firm evolves as a Brownian motion. In the event of a default the firm's total value is lower than its debt at the date of maturity and the firm's assets are transferred from the shareholders to the bondholders. Otherwise, debt is repaid and the shareholder receive the firm's assets. The pay-off structure implies that equity can be viewed as a European call option on the firm's assets with strike price equal to the value of debt. Put differently, debt is equivalent to a long position in a risk-free bond and a short position in a European put option with strike price equal to debt. The CDS as a standardized product allows the bondholder to hedge against the risk of this short position. Therefore, prices of CDS (often termed 'CDS spreads') are driven by the well-known standard option pricing variables, i.e. the strike price (debt level), the current asset price (firm value), asset price volatility, and the risk-free rate. Thus, the expected CDS spread increases if the debt level rises or if the firm value declines. Furthermore, the CDS spread increases if the volatility of the firm's equity increases. The reason is the higher probability that the firm will hit eventually the default barrier. The risk-free interest rate represents the drift in the firm value, a higher interest increase the future expected value and therefore reduces CDS spreads. As a result and following the Merton (1974) model, the standard linear panel pricing equation regresses CDS spreads $y_{i,t}$ for firm $i = 1, 2, ..., N$ and week $t = 1, ..., T$ on fixed effects μ_i and the vector $X_{i,t}$ containing the risk-free interest rate (RFR), the asset value, the asset volatility and the debt level of the respective firm:

$$y_{i,t} = \mu_i + \beta' X_{i,t} + u_{i,t} \tag{1}$$

The unconditional estimates of parameter coefficients in β' represent sample-specific averages and do not account for the possibility of a regime shift resulting from a change of the market environment. However, this is likely to happen, because, as has been observed in the 2000s, investors' risk appetite exhibits substantial swings thereby altering CDS pricing coefficients. Since it is not only agents' perceptions of risk which may account for a transition towards a different pricing regime we will test for a number of exogenous market indicators potentially influencing β', i.e. the weekly published systemic stress composite (SYS) index form the European Central Bank, the Sentix index for the current (ICS) and future economic situation (IFS), the EURO STOXX 50 average (ESA) and the 5-year swap rate, and the VStoxx (implied volatility from EURO STOXX 50 options).[4]

The flexibility of the β' vector to evolve over time introduces a strong nonlinearity into the relationship between CDS spreads and their pricing variables. We assume that

[4]We denote the regressors in $X_{i,t}$ by pricing variables and transition variables influencing the β vector by market indicators. A detailed description of all variables is provided in the data section.

these parameter changes occur in a systematic fashion and describe a smooth parameter transition between two or more regimes of the model. Under these circumstances the application of the (Panel) Smooth Transition Regression (PSTR) model originally proposed by González et al. (2005) provides a useful econometric framework to estimate the CDS pricing equation and to test for the influence of the transition variables.[5] Our PSTR model is defined as

$$y_{i,t} = \mu_i + \beta_0' X_{i,t} + \sum_{j=1}^{J} \beta_j' X_{i,t} g_{j,t}(q_t; \gamma_j, c_j) + u_{i,t}, \tag{2}$$

for firm $i = 1, 2, ..., N$ and week $t = 1, ..., T$. The constants μ_i again capture individual effects and $g_{j,t}(q_t; \gamma_j, c_j)$ is one of j functions which determine the transition between the $J + 1$ different regimes. The logistic transition function is defined as

$$g_{j,t}(q_t; \gamma_j, c_j) = \left(1 + \exp\left(-\gamma_j \prod_{r=1}^{R} (q_t - c_{j,r})\right)\right)^{-1}, \tag{3}$$

where $c_{j,r}$ is one of R location parameters, γ_j is the speed of transition between regimes and q_t is the composite transition variable in transition function $g_{j,t}(q_t; \gamma_j, c_j)$. The transition function is bounded between 0 and 1 resulting in regression coefficients bounded between β_0 and $\beta_0 + \beta_1$, respectively. The parameter r defines the specific functional form with which the composite transition variable enters the logistic function. For instance, if $r = 2$, the transition function $g_{j,t}(q_t; \gamma_j, c_j)$ is symmetric around the location parameters. The coefficient γ determines the speed of transition including the corner solution $\gamma \to \infty$, where the panel smooth transition model converges towards the threshold panel model of Hansen (1999). It is also interesting to notice that for $\gamma \to 0$ the model collapses to a standard fixed effects model. As a result the PSTR model is nesting more traditional econometric frameworks used in the literature.

Our empirical approach of eq. (2) and (3) goes beyond the basic PSTR model of González et al. (2005) in two respects. Firstly, we consider a composite (multivariate) transition variable as proposed by Lof (2012). The composite transition variable $q_t = Q_t\lambda$ may consist of up to p different transition variables $Q_t = [q_{1,t}...q_{P,t}]$. This allows for a number of different market indicators to determine the transition between the model's regimes. Due to the presence of γ_j the coefficients contained in λ are restricted to sum up to unity (Lof, 2012). Given that transition variables enter Q_t as standardized values the composite transition variable $Q_t\lambda$ can be viewed as a weighted sum of regime-determining indicators.

[5] As will be shown later the transition between regimes is also allowed to take place in an abrupt fashion as a corner solution of the more general smooth transition.

In the basic PSTR model a single transition function is specified for all variables in $X_{i,t}$ and thus restrict the parameters γ_j and c_j to be equal across all regressors. However, we have no a priori knowledge if this assumptions holds. Different parameters would not come as a surprise because some of our variables react quickly to changing conditions in the market (close prices) while others react with greater lags (debt ratio). The same logic applies for the location parameters c_j and weights λ in case of multivariate transition functions. The second extension therefore considers transition functions to be heterogeneous across variables in X to account for different parameter values.

We therefore rewrite equation (2) to

$$y_{i,t} = \mu_i + \sum_{k=1}^{K} \beta_{0,k} x_{k,i,t} + \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{j,k} x_{k,i,t} g_{j,k}(q_{k,t}; \gamma_{j,k}, c_{j,k}) + u_{i,t}. \tag{4}$$

Since $q_{k,t} = Q_{k,t}\lambda_k$ the transition function for regime j now depends on a linear combination of a number of market indicators and is defined as

$$g_{j,k}(q_{k,t}; \gamma_{j,k}, c_{j,k}) = \left(1 + \exp\left(-\gamma_{j,k} \prod_{r=1}^{R} (Q_{k,t}\lambda_{j,k} - c_{j,k,r})\right)\right)^{-1}. \tag{5}$$

This additional flexibility of the model ensures that the importance of a single transition variables in $Q_{k,t}$ measured by its estimated weight in λ can change over different regressors in $X_{i,t}$.[6] According to González et al. (2005) the implementation of the model is carried out in three steps: (i) specification, (ii) estimation, and (iii) evaluation.

Specification

The first step is to test linearity against the PSTR alternative. We carry out separate tests for each variable in X_t and if linearity cannot be rejected, the variable is included as a linear explanatory variable in our model. Due to the structure of the model we cannot apply a simple t-test on $\gamma_{j,k}$ because of the presence of unidentified nuisance parameters under the null hypothesis of $\mathrm{H}_0 : \gamma_{j,k} = 0$. To circumvent this problem we follow Luukkonen et al. (1988) and replace the transition function by its first-order Taylor expansion around $\gamma_{j,k} = 0$ to derive the auxiliary regression

$$y_{i,t} = \mu_i + \beta'^{*}_{0,k} x_{k,i,t} + \beta'^{*}_{1,k} x_{k,i,t} q_{k,t} + ... + \beta'^{*}_{m,k} x_{k,i,t} q^{m}_{j,k,t} + u^{*}_{i,t} \tag{6}$$

where $\beta'^{*}_{1,k} ... \beta'^{*}_{m,k}$ are multiples of γ_k. Testing $\mathrm{H}^{*}_0 : \beta'^{*}_{1,k} = ... = \beta'^{*}_{m,k} = 0$ in the auxiliary regression is equivalent to testing $\mathrm{H}_0 : \gamma_{j,k} = 0$. The test is carried out by applying the

[6] In a few cases we set a specific $\lambda_i = 0$ to ensure convergence of the estimation routine.

robust LM-test derived by González et al. (2005).

The test procedure is easily applied if the transition function is univariate. However, in case of a multivariate transition function equation (6) cannot be estimated if weights λ are unknown. We derive the required weights by substituting $q_{j,k,t} = Q_{k,t}\lambda_{j,k}$ into a first-order version of equation (6)

$$y_{i,t} = \mu_i + \beta_{0,k}^{\prime *} x_{k,i,t} + \beta_{1,k}^{\prime *} x_{k,i,t}(Q_{k,t}\lambda_{1,k}) + u_{i,t}^{*} \tag{7}$$

and rewriting equation (7) to

$$y_{i,t} = \mu_i + \beta_{0,k}^{\prime *} x_{k,i,t} + \sum_{l=1}^{p} \phi_{k,l} x_{k,i,t} q_{k,l,t} + u_{i,t}^{*} \tag{8}$$

with $\phi_{k,l} = \beta_{1,k}^{\prime *}\lambda_{k,l}$. The parameters λ can be identified with the use of the restriction $\sum_{l=1}^{p} \lambda_{k,l} = 1$. To see this, note that

$$\sum_{l=1}^{p} \phi_{k,l} = \beta_{1,k}^{\prime *} \sum_{l=1}^{p} \lambda_{k,l} = \beta_{1,k}^{\prime *} \Rightarrow \lambda_{k,m} = \left(\sum_{l=1}^{p} \widehat{\phi}_{k,l} \right)^{-1} \widehat{\phi}_{k,m}. \tag{9}$$

The estimated weights λ of equation (9) are used to test for nonlinearity.

Irrespective of the specific type of the transition function, univariate or multivariate, the test procedure against nonlinearity can be used to select the appropriate order r of the k transition functions by testing $\mathrm{H}_{03}^{*} : \beta_3^{*} = 0$, $\mathrm{H}_{02}^{*} : \beta_2^{\prime *} = 0 | \beta_3^{\prime *} = 0$ and $\mathrm{H}_{01}^{*} : \beta_1^{\prime *} = 0 | \beta_3^{\prime *} = \beta_2^{\prime *} = 0$. Following Teräsvirta (1994), $R = 2$ is chosen if the rejection of H_{02}^{*} is the strongest, otherwise $R = 1$ is chosen.

Estimation

The estimation of parameters in the PSTR consists of applying alternately fixed effects and nonlinear least squares. Equation (4) is a linear function of β if $\gamma_{j,k}, c_{j,k}$ and $\lambda_{j,k}$ are known for each transition function k. Estimation is carried out by ordinary least squares after demeaning the data. However, the estimated means depend on $\gamma_{j,k}, c_{j,k}$ and $\lambda_{j,k}$ as well and have to be re-estimated at each iteration. The parameters of the transition functions are estimated by nonlinear least squares if β_k's are given. This is done separately for each transition function so that K nonlinear least squares optimization have to be carried out.[7] The alternately estimation procedure is carried out until every numerical optimization of the nonlinear least squares model converged. A standard

[7] It is possible to jointly estimate all parameters for the K transition function in one NLS model. However, the separate estimations proved to be less time consuming. Furthermore, this procedure allows us to switch off temporary converged NLS optimizations which saves us a lot of estimation time without changing the overall result.

necessity of PSTR estimation is the choice of appropriate starting values for $\gamma_{j,k}$ and $c_{j,k}$. We perform an extensive grid search across the parameters in the transition function. If required, starting values for $\lambda_{k,l}$'s are provided by equation (9) after the nonlinearity tests.

Evaluation

After estimation, the results are evaluated by testing for parameter constancy and no remaining nonlinearity. Both tests are conceptual similar to the above tests against linearity. Thus, again a Taylor expansion around $\gamma = 0$ is used to test for parameter constancy evaluating the null hypothesis of the PSTR against the alternative of a time varying panel smooth transition model (TV-PSTR). Under the alternative, the parameter are assumed to change smoothly over time by a transition function similar to (3) with time as the transition variable. The test for remaining nonlinearity is carried out separately for each transition function and is used to evaluate if the PSTR is able to fully capture the present nonlinearity in the data.

4 Data

We use 5-year CDS spreads written on senior debt from EURO STOXX 50 firms.[8] The information on CDS spreads are extracted from Thomson Datastream as annualized spreads in basis points. Our sample covers the period from January 2004 to September 2013 with a weekly frequency which allows us to evaluate the behavior of single name CDS spreads during the crisis and in non-crisis periods. We follow Wang et al. (2013) and Tang and Yan (2010) by using levels instead of first differences. This is further supported by the choice of our model. It is unknown if the properties of the PSTR still holds if first differences are applied instead of fixed effects. Instead of the means, the differences would depend on the estimated parameters from the transition function.

– Insert Figure 1 here –

Figure 1 depicts the the average CDS spreads from EURO STOXX 50 firms over time. Two main periods of strongly increasing CDS spreads for EURO STOXX 50 firms can be observed. The first is directly related to the sub-prime crisis originated in the US while the second refers to the Euro area crisis with raising concerns about financial stability and the dwindling economic outlook for the area.

The choice of explanatory variables in the CDS pricing equation is made in accordance to literature.[9] Since not all postulated variables of the Merton model are observable we

[8]Definition refers to 31. October 2013.

[9]The most important drivers were already introduced in section 3.

have to resort to proxies. For the unknown firm value, we use information on firms' stock prices (close prices CS), while the asset volatility is approximated by the volatility of firms' equity (EV). We use the annualized exponential weighted moving average of squared stock returns as a measure of firms' asset volatility. Furthermore, we include the leverage ratio (LR) of each firm defined as total liabilities divided by total assets. The information on firms' balance sheets are taken from Macrobond. Since balance sheet information are released on a quarterly (or semi-annual) basis, we use a linear interpolation to derive at weekly frequency. The risk-free interest rate is modeled by Euro swap rates with five years to maturity to match the 5-year horizon of the CDS spreads. The swap rate represents the rate that buyers are willing to exchange against the floating 5-year Euribor. We resort to swap rate rather than government bonds to model the risk-free interest rate since they are regarded as a better proxy (Houweling and Vorst, 2005).

Apart from the variables required by the Merton model, we include two further variables which are commonly applied to explain credit default swaps spreads. The slope of the yield curve (YC) is used frequently, e.g. in Alexander and Kaeck (2008), Annaert et al. (2013), Cesare and Guazzarotti (2010) and Ericsson et al. (2009). The yield curve is supposed to capture the business cycle, a steeper curve can be interpreted as an indicator of improving economic situations in the future which is in general accompanied by higher interest rates. However, the exact direction of influence is unclear (Galil et al., 2014). An increasing yield curve reflects improving economic conditions which should lead to lower CDS spreads. But at the same time, the number of possible projects with positive net present value is reduced which might cause a deterioration of the firms' outlook and therefore increasing CDS spreads.

The second additional variable captures information on market volatility (VStoxx implied volatility index) as a proxy for market wide risk, applications can be found in Breitenfellner and Wagner (2012), Collin-Dufresne et al. (2001), Cesare and Guazzarotti (2010) and Galil et al. (2014). We expect a positive relation to CDS spreads. All times series contained in $X_{i,t}$ consist of contemporaneous weekly observations.

The main contribution of this paper is to allow these pricing variables to influence CDS spreads in a different way during times of financial distress. Thus, the above regressors are suspect to exert a *conditional* influence as different regimes of the market environment may alter their relationship with CDS spreads. The panel smooth transition regression model allows us to specify and test for variables which drive the transitions between regimes. Since we are interested in capturing swings in market participants' perception of risk we consider the following transition variables in the model. The first candidate is the weekly published systemic stress composite (SYS) index form the European Central Bank. The index covers the stress level in five different markets, that is the sector of bank and nonbank financial intermediaries, money markets, securities markets and foreign exchange markets. A detailed description can be found in Holló et al. (2012). Furthermore, we use the Sentix index for the current (ICS) and future economic situation (IFS). Information on investors sentiment are found to be helpful in the context of CDS spreads (Tang and Yan (2010)). The variables are based on surveys among investors in the eurozone about their expectation of the current and the six-month-ahead economic situation. We convert them to weekly data by carrying the last observation forward. Closely related are the variables on the consumer confidence indicator and the industrial confidence indicator. Moreover, we test the EURO STOXX 50 average (ESA) and the 5-year swap rate. Finally, the VStoxx (implied volatility from EURO STOXX 50 options) is introduced as the European counterpart of the VIX, the standard global measure of investors' risk perception. The following Table 1 provides descriptive statistics of all variables.

– Insert Table 1 here –

5 Results

Referring to estimation cycle of PSTR models we first discuss the results of tests for linearity. As a starting point univariate transition functions approximated by Taylor expansion series were tested separately for each regressor in $X_{i,t}$. The test statistics can be found in table 2 in columns two to six.

– Insert Table 2 here –

The results show that linearity cannot be rejected for every combination of transition variables and explanatory variables. Different transition variables tend to govern non-linear transitions for different explanatory variables. For the systemic stress index, for instance, linearity is strongly rejected with respect to the leverage ratio and the yield curve, while linearity prevails for equity volatility. The Sentix indicator of the current economic situation shows strong nonlinearity with respect to the close prices and to a lesser extend to the equity volatility and the leverage ratio. The yield curve, VSToxx and the risk-free interest rate reveal significant rejections of the null hypothesis as well. Since testing potential transition variables separately for each regressor does not reveal a clear picture regarding their importance in capturing nonlinearities we assess their ability to jointly influence the βs of all regressor in $X_{i,t}$. The test statistics listed in column 2 represent the results of the joint linearity test of the specific transition variable with respect to all variables in $X_{i,t}$ serving as a means to assess the overall ability to govern a non-linear relationship in the CDS pricing equation. We proceed with the five variables where linearity is most strongly rejected, i.e. the EUROSTOXX 50 continuous average, systemic stress, Sentix indicator of current and future situations and the risk-free interest rate. We combine these variables in a multivariate transition function and test for linearity with respect to the CDS pricing variables. As outlined in section 3 the required weights for the multivariate linearity tests have to be derived first. Results for the tests are listed in table 3 alongside with the weights.

– Insert Table 3 here –

We start with the systemic stress and add consecutively variables to the transition function. As expected, the rejection of linearity for the explanatory variables becomes stronger with additional transition variables. The last specification is our preferred one because of highest χ^2-test statistics.[10] We proceed by estimating the PSTR model with the five selected variables in the multivariate transition function with the exception of the transition function for the risk free rate, which is composed of only four transition variable. All transition variables enter as standardized values into the transition function in order to facilitate the interpretation of the estimated weights.[11] Furthermore, we include these variables as additional (linear) explanatory variables in the PSTR model (in a non-standardized version) in order to account for direct effects on CDS spreads. The specification tests also suggest that a PSTR model with two regimes ($j = 1$ in eq. (2)) with linear transition functions ($r = 1$ in eq. (3)) is sufficient in order to model the detected nonlinearities.[12]

Table 4 contains the estimated coefficients of the multivariate PSTR. All variables with regime depended coefficients show significant β_0 and β_1 in both regimes. Firms' leverage ratios are negatively related to CDS spreads in the first regime whereas the second regime is governed by a positive relation.

– Insert Table 4 here –

Figure 2(a) illustrate this graphically. The estimated coefficient changes smoothly from negative to positive with increasing value of the transition variable. The estimated λ's represent the weights of the corresponding variable for the transition from one regime to another. The main positively (negatively) driving variable for the transition is the indicator of the current situation (EURO STOXX 50 index) with $\lambda_2 = 224528.33$ ($\lambda_5 = -45828.68$). In general, increasing CDS spreads through higher leverage ratios are found when the second regime prevails, which is the case with high systemic stress, high indicator

[10]Note that we refrain from including the risk-free interest rate as transition variable with respect to itself due to stability problems of estimation.
[11]The estimated betas are unaffected by standardization of transition variables.
[12]Note that we test for no remaining nonlinearities in the evaluation section of the paper.

for the current economic situation, low level for the future economic situation, high risk-free interest and a low EURO STOXX 50 index.

– Insert Figure 2 here –

Figure 3 (a) plots the estimated coefficient over time which reveal interesting pattern over time. In the run-up to the crisis, leverage ratios are negatively correlated with CDS spreads coinciding with the first regime. This result might be driven by the fact that in the period between 2004 and mid 2007 investors' risk appetite was exceptionally high leading to high leverage ratios and low CDS spreads at the same time. The reason might be that markets honor expansionary firm strategies which are often accompanied by increasing leverage ratios. During good times the expected higher future earnings of the risky strategy might prevail which lowers CDS spreads. During crisis periods, however, the second regime with a high positive beta coefficient prevails. The two peaks indicate the worsening of the crisis, the Lehman Brothers bankruptcy and the Greece haircut. Within this regime, higher leverages are associated with higher CDS spreads in line with the expected direction of influence reflecting that increasing leverage ratios are now connected with severe liquidity problems of the firm.

– Insert Figure 3 here –

Close prices as well exhibit a change in the sign of the estimated coefficient from one regime to the other. In the first regime there is a negative relationship between close prices and CDS spreads, as expected, while in the second regime an increase in the share prices is associated with increasing CDS spreads. The main driving variables in the transition function of close prices coefficient are the index of current and future situations with weights equal to -0.359 and 0.463, respectively. The first regime is described by high levels of systemic stress, high levels of investors sentiment about the current economic situation and low levels of investors sentiment for the future situation. Moreover, a low risk-free interest rate and low a low level of the EURO STOXX 50 characterize the first regime. As indicated by Figure 3(b) positive β coefficients are found mainly before the first peak of the crisis. The following periods again show a negative relation where increasing close prices lead to decreasing CDS spreads, as suggested by the baseline theoretical model. Using differences rather than levels and time-series data rather than panel data, Breitenfellner and Wagner (2012) found as well changing relations (between the return and the non-financial iTraxx index for Europe). In the pre-crisis period (June 16, 2004 to July 2, 2007), the return negatively influences the non-financial iTraxx index for Europe while it shows a positive but insignificant coefficient during the crisis. The last period is characterized again by a strong negative influence. However, our result differ by reversed signs for the pre-crisis and crisis period.

In accordance with the model a positive influence of firm specific equity volatility on CDS spreads is found for both regimes. This implies that an increase in equity volatility coincides with increase in firms' CDS spreads. While the first regime shows an estimated β_0 of 123.7 the second is characterized by a negative (-122.7) coefficient. Since the negative coefficient is lower in absolute value than β_0 a positive but small coefficient appears in the second regime (with coefficient equal to $\beta_0 + \beta_1 g$).

The transition between regimes occurs sharply as Figure 2c reveals. The Sentix index of current situation (0.587) is the main driver followed by EURO STOXX 50 (0.463), the risk-free rate (-0.070), the Sentix index of future situation (0.036) and the systemic stress (-0.009). The first regime with significantly higher βs occurred at the peaks of the crisis (3c). Shortly before (after), the model jumps from (back to) regime two. Separating between crisis and a non-crisis period the signs of the transition variables are as expected. The only exception might be the negative sign of the risk-free rate. Apparently, a high risk-free rate is required (c.p.) to stay in the (crisis) regime one, but usually bust cycles are accompanied by low interest rates. However, interest rates are guided by central banks which react only with lags to a crisis.

The results for the yield curve reveal different relations between the variable and CDS spreads in the two regimes. While in regime 1, we find a negative beta which change smoothly towards positive values in regime two. In case of the yield curve, the generated transition variable in the transition function is positively affected by the Sentix indicator of current and future situations as well as the risk-free rate. The systemic stress and the EURO STOXX 50 enter negatively positively. The highest effects on the regime switch have the Sentix indicator of future situations (1432) and the ECB measure of systemic risk (-1073.58). An increase of the yield curve lowers the CDS spreads given that most variables are in unfavorable states, i.e. high stress and low levels of investors sentiment (current and future) and a low interest rate. We find support for both previously stated possibilities for the direction of influence. The transition takes place smoothly over the range of the generated transition variable. Figure 3d display that the yield curve has a negative influence mainly during peaks of the crisis. In non-crisis times, we find an CDS increasing effect of the yield curve.

For the risk-free interest rate, signs differ between β_0 and β_1 as well. However, both regimes are governed by negative influences of the risk-free interest rate on CDS spreads which is in accordance with theory. The reason is the small magnitude of the estimated coefficients for β_1 (75.375) compared to β_0 (-105.027) which does not suffice to produce overall positive values for the influence even if the transition function approaches unity.

The least negative value for the estimated coefficient can be found from 2006 onwards until the first peak of the crisis, as figure 3e depicts. The two peaks of the crisis are characterized by sharply decreasing trends for the coefficient. As mentioned before, the transition for the risk-free interest rate is governed only by four instead of five transition variables since we decided not to include the risk-free rate both in $q_{5,t}$ and $X_{5,i,t}$ at the same time.[13] The transition towards the second regime is driven by high levels of systemic stress, EURO STOXX 50 index and the Sentix indicator for the current situations. Only the Sentix indicator for the six month ahead situation enters negatively.

Very limited influences of regime changes can be observed for market volatility, measured by the VStoxx. During most of the time, the estimated coefficient remains negative but close to zero. The first regime with positive values is entered only in few periods which coincide with the first and second peak of the crisis (Figure 3f). Again, the transition occurs in an abrupt fashion with a high estimated γ suggesting a threshold-type relationship. The changing sings of market volatility in different regimes confirm the finding of other works on CDS spreads. Using a Markov switching regression for the European non-financial iTraxx-index, Alexander and Kaeck (2008) found a small negative influence of the VStoxx on the CDS index during tranquil times and a high positive influence during their volatile regime which coincide with our finding for individual firm-level CDS spreads. Wang et al. (2013) found negative market-wide volatility influences on US firms' CDS spreads in the period 2001-2006 while controlling for a bunch of other variables and positive (but not significant) influences 2007-2011. Somewhat similar results are found by Annaert et al. (2013) for financial CDS spreads. In the pre-crisis period, the coefficient for the market wide volatility fluctuates around zero, becoming positive after the start of the crisis but approaches negative values in 2009.

The last step of the panel smooth transition regression is the evaluation of the model. Table 5 reports the results.

– Insert Table 5 here –

Firstly, we test for no remaining nonlinearity for each variable in $X_{i,t}$ with respect to the previously applied transition variables. The LM-test is conceptual similar to the specification tests and evaluates whether the model is able to fully capture the nonlinearity in the data. The results indicate that there are no remaining nonlinearities in our model with heterogeneous transition functions for all specified variables. The second test evaluates if the estimated βs vary over time. The χ^2 test statistic shows signs of changing parameters over time, which indicate that the model does not fully account for regime changes over time. The latter interpretation is valid if we refrain from assuming

[13]Therefore, weight $\lambda_5 = 1 - \lambda_1 - \lambda_2 - \lambda_3$.

the existence of an unspecified nonlinear time trend in CDS pricing but rather a missing factor in the transition functions, which is not taken into account. Nevertheless, we are able to dramatically reduce the χ^2 test statistic from 1071.15 after a linear fixed effects model to 199.98 after the estimation of the PSTR model. With respect to the goodness of fit we find that the PSTR model explains 63.5 % of the variation in our data which is a significant increase over a linear fixed effects model with an R^2 of 50.7%. Altogether, we conclude that the panel smooth transition regression model with the selected transition variables is a reasonable choice for the modelling of regime changes in the pricing equation of CDS spreads during times of crisis.

6 Conclusion

In academic circles as well as in the policy arena it has been argued that the switch from overly optimistic to dramatically pessimistic sentiment of investors contributed to the enormity of the 2008 global financial crisis. This behavior of financial market participants also seemed to prevail during the European government debt crisis when government bond spreads appear to be negligible before and extraordinarily elevated after the Greek near-default. From a theoretical perspective this observation suggests that a time-varying perception of risk should lead to a regime-dependent pricing of asset. This paper provides empirical evidence on the importance of time-varying risk perception by investigating the impact of a changing market environment on the pricing of CDS spreads written on debt from EURO STOXX 50 firms. A Panel Smooth Transition Regression reveals that parameter estimates of standard CDS fundamentals depend on a set of crisis-related variables such as the ECB's systemic stress composite index, the Sentix index for current and future economic situation, and the VStoxx. These variables are expected to reflect substantial swings in agents' risk perception when pricing CDS spreads. The estimation of a multivariate transition function including these transition variables and the identification of the required weights substantially increases the flexiblity of the model. Further extension of the (multivariate) panel smooth transition regression model allows for heterogeneous transition functions implying that different pricing variables may interact with different transition variables. Overall, our results confirm the importance of nonlinearities in the pricing of risk derivatives during tranquil and turbulent times.

Table 1: Summary statistics

	Obs.	Mean	Std.	Min.	Max.
Credit default swap spread	10826	87.044	75.823	4.84	595
Leverage ratio (LR)	10826	0.655	0.1278	0.082	1
Close price (CS)	10826	37.942	29.863	2.128	202.94
Equity volatility (EV)	10826	0.217	0.146	0.009	2.367
Yield curve (YC)	10826	1.202	0.782	-0.434	2.618
Risk-free interest rate (RFR)	10826	2.785	1.168	0.732	5.15
Market volatility (VStoxx)	10826	25.064	9.783	12.026	71.494
Systemic stress (SYS)	10826	0.290	0.201	0.024	0.827
Index of current situation (ICS)	10826	-0.455	31.225	-59.75	65
Index of future situation (ICF)	10826	-2.523	16.556	-42.75	33.25
EURO STOXX 50 (ESA)	10826	2979.643	658.735	1825.26	4583.78

Table 2: Linearity test: univariate transition function

q	Joint	LR	CS	EV	YC	RFR	VSToxx
Systemic stress	616.18	291.05	88.50	1.35	122.90	26.31	5.41
Sentix current situation	651.35	69.87	427.51	71.07	19.19	4.87	11.36
Sentix future situation	546.27	265.36	194.69	2.53	1.31	10.99	0.25
EURO STOXX 50 average	942.52	138.38	551.50	9.50	116.70	126.96	36.25
Risk-free interest rate	572.11	0.04	455.39	18.34	80.87	105.87	0.25
Inflation surprise	224.12	6.55	5.53	40.76	168.79	47.96	71.12
Commodity tot	333.56	25.25	42.34	82.09	163.71	77.53	188.36
Economic Surprise	330.04	128.71	103.86	27.12	10.43	15.02	3.34
VStoxx	521.12	182.05	130.62	54.90	1.51	0.25	129.17
Yield curve	244.06	0.31	148.34	4.57	96.78	80.87	1.51

Note: χ^2-statistics for linearity test. The 5% critical value for the joint test (column 2) is 12.591, for single regime dependent variables 3.841 (column 3-8).

Table 3: PSTR with univariate transition function

	NL-test		Estimated weights				
x	χ^2	p	λ_1	λ_2	λ_3	λ_4	λ_5
Q = *SYS*							
Leverage ratio	291.050	0.000	.	.	.	.	.
Close price	88.504	0.000	.	.	.	.	.
Equity volatility	1.335	0.248	.	.	.	.	.
Yield curve	122.901	0.000	.	.	.	.	.
Risk-free rate	26.307	0.000	.	.	.	.	.
Market volatility	5.408	0.0200	.	.	.	.	.
Q = *SYS, ICS*							
Leverage ratio	295.343	0.000	0.990	0.010	.	.	.
Close price	367.556	0.000	1.180	-0.180	.	.	.
Equity volatility	84.734	0.000	0.852	0.1478	.	.	.
Yield curve	135.957	0.000	1.030	-0.030	.	.	.
Risk-free rate	46.454	0.000	0.941	0.059	.	.	.
Market volatility	55.078	0.000	0.921	0.079	.	.	.
Q = *SYS, ICS, IFS*							
Leverage ratio	311.268	0.000	1.0735	0.014	-0.088	.	.
Close price	389.589	0.000	0.482	0.205	0.314	.	.
Equity volatility	93.615	0.000	0.858	0.062	0.080	.	.
Yield curve	79.598	0.000	0.927	0.002	0.072	.	.
Risk-free rate	101.084	0.000	0.953	0.114	-0.067	.	.
Market volatility	101.328	0.000	0.876	0.042	0.082	.	.
Q = *SYS, ICS, IFS, RFR*							
Leverage ratio	322.631	0.000	1.746	0.040	-0.118	-0.667	.
Close price	630.243	0.000	-0.188	-0.014	0.034	1.167	.
Equity volatility	120.199	0.000	1.704	0.128	0.130	-0.961	.
Yield curve	123.907	0.000	0.273	-0.011	0.040	0.699	.
Risk-free rate	101.084	0.000	0.952	0.114	-0.067	.	.
Market volatility	143.876	0.000	3.432	0.196	0.251	-2.879	.
Q = *SYS, ICS, IFS, RFR, ESA*							
Leverage ratio	321.715	0.000	0.754	0.038	-0.066	0.277	-0.002
Close price	665.981	0.000	-0.159	-0.017	0.036	1.140	0.000
Equity volatility	116.469	0.000	0.902	0.098	0.090	-0.088	-0.002
Yield curve	151.330	0.000	0.346	-0.014	0.041	0.626	0.001
Risk-free rate	255.354	0.000	0.980	0.079	-0.063	.	0.004
Market volatility	154.145	0.000	1.718	0.134	0.146	-0.997	-0.003

Note: χ^2-statistics for multivariate test of linearity.

Table 4: Estimation results of the multivariate PSTR model

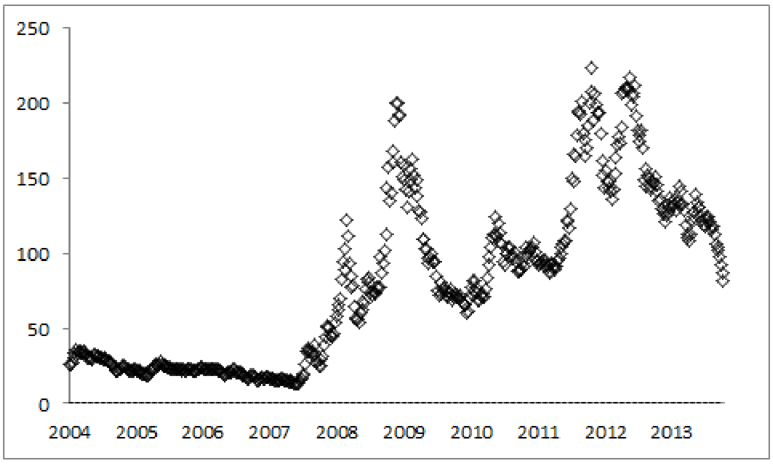
$x_{i,t}$	β_0	β_1	γ	c	λ_1	λ_2	λ_3	λ_4
Regime dependent variables								
Leverage ratio	-146.090	344.990	0.000	36609.95	22473.44	24528.33	-21092.83	19920.74
	(63.025)	(58.878)	(0.000)	(.)	(801.682)	(996.85)	(833.382)	(1036.81)
Close price	-1.239	2.112	1.717	0.117	-0.193	-0.359	0.463	0.807
	(0.382)	(0.682)	(0.010)	(0.028)	(0.039)	(0.037)	(0.014)	(0.060)
Equity volatility	123.725	-122.731	11.257	-0.923	-0.009	0.587	0.036	-0.070
	(21.199)	(22.245)	(1.651)	(0.070)	(0.044)	(0.040)	(0.024)	(0.036)
Yield curve	-804.011	850.163	0.000	-9318.37	-1073.58	266.248	124.187	1432.015
	(135.274)	(141.217)	(0.000)	(.)	(24.390)	(33.206)	(38.998)	(42.619)
Risk-free rate	-105.027	75.375	1.317	-0.065	0.332	0.400	-0.309	.
	(18.558)	(15.795)	(0.039)	(0.021)	(0.005)	(0.013)	(0.020)	(.)
Market volatility	1.327	-1.671	7.075	-1.966	0.072	0.690	1.085	0.362
	(0.628)	(0.454)	(1.403)	(0.179)	(0.043)	(0.190)	(0.059)	(0.055)
Other variables								
Systemic stress	-19.886	.	.	.	.	.	.	.
	(24.924)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
ICS	-0.852	.	.	.	.	.	.	.
	(0.2603)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
IFS	1.128	.	.	.	.	.	.	.
	(0.311)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
ESA	-0.0109	.	.	.	.	.	.	.
	(0.0148)	(.)	(.)	(.)	(.)	(.)	(.)	(.)

Note: Robust standard errors in parentheses; λ_5 is given by $1 - \lambda_1 - \lambda_2 - \lambda_3 - \lambda_4$. λ_1 = systemic stress, λ_2 = Sentix current situation, λ_3 = Sentix future situation, λ_4 = risk free rate, λ_5 = EURO STOXX 50 average

Table 5: Model evaluation

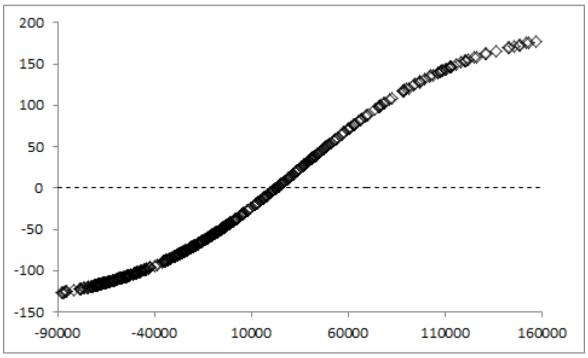
	Full model	Transition functions					
		$g_{1,1}$	$g_{1,2}$	$g_{1,3}$	$g_{1,4}$	$g_{1,5}$	$g_{1,6}$
No remaining nonlinearity		0.0944	0.0078	0.5363	0.0174	0.0610	2.695
Parameter constancy	199.512						
R^2	0.635						

Figure 1: Average CDS spreads over time

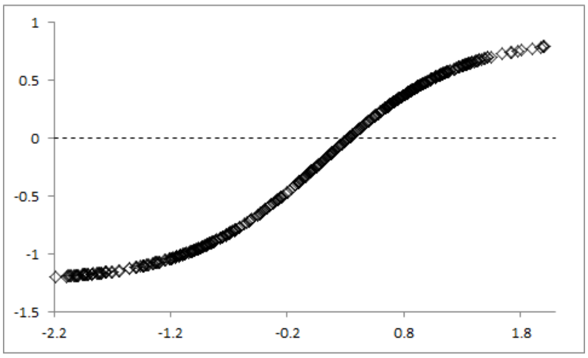


Note: Time (in weeks) on the horizontal axis, average CDS spreads (basis points) on the vertical axis.

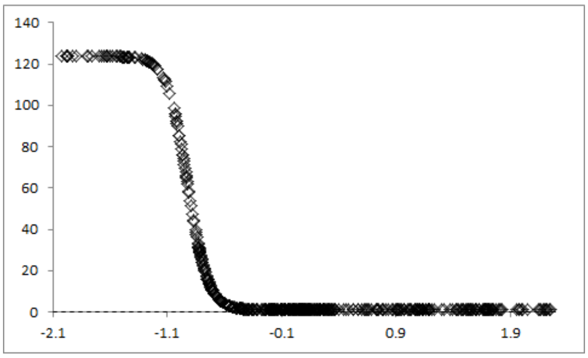
Figure 2: Multivariate transition function: part one



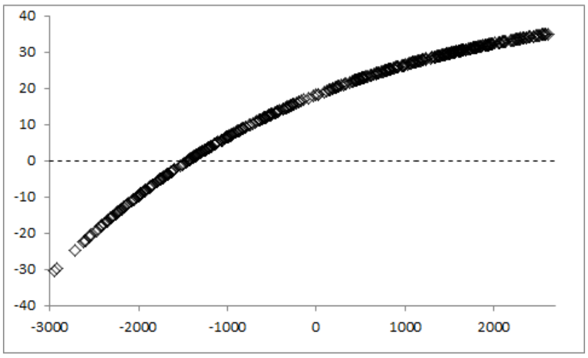
(a) Leverage ratio



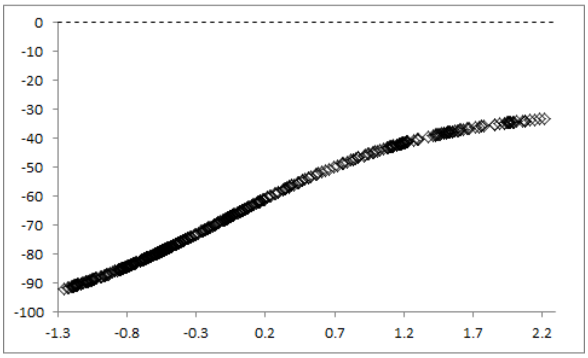
(b) Close price



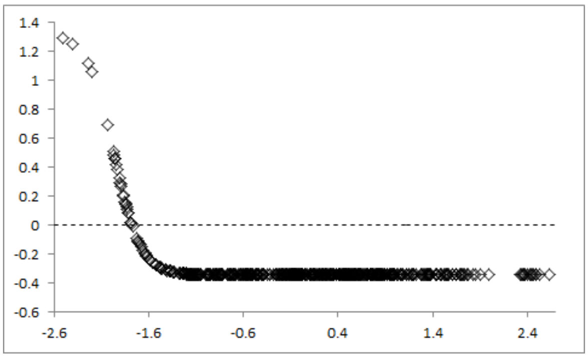
(c) Equity volatility



(d) Yield curve



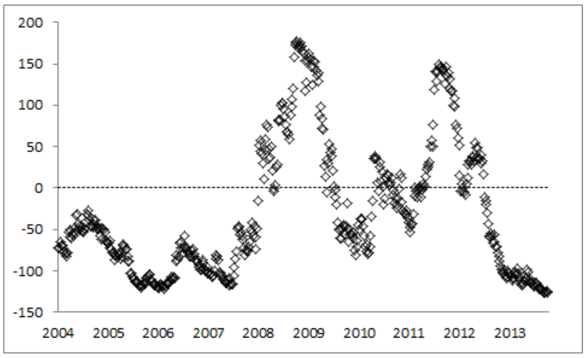
(e) Risk free rate



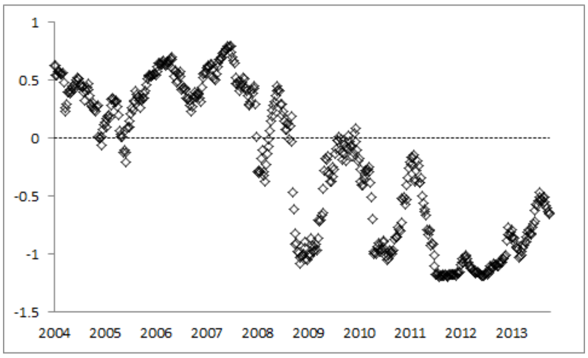
(f) Market volatility

Note: Transition variable $(\lambda_{k,1}q_{k,1,t} + \lambda_{k,2}q_{k,2,t} + \lambda_{k,3}q_{k,3,t} + \lambda_{k,4}q_{k,4,t} + \lambda_{k,5}q_{k,5,t})$ on the horizontal axis; estimated parameters $(\beta_{0,k} + \beta_{1,k}g_{1,k})$ on the vertical axis.

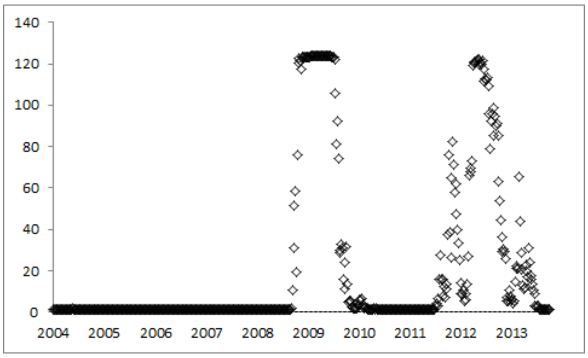
Figure 3: Multivariate transition function: part two



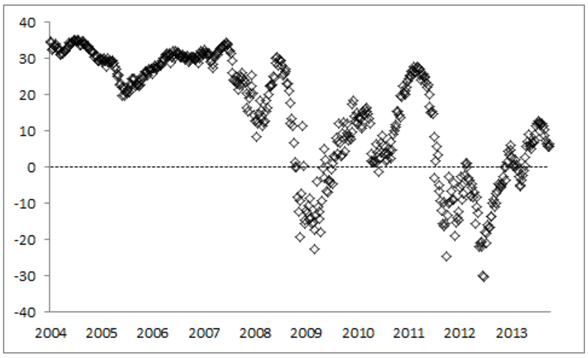
(a) Leverage ratio



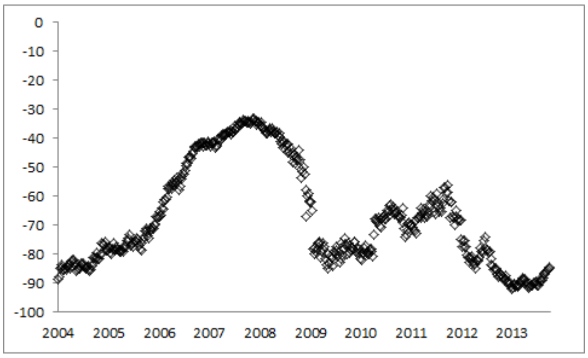
(b) Close price



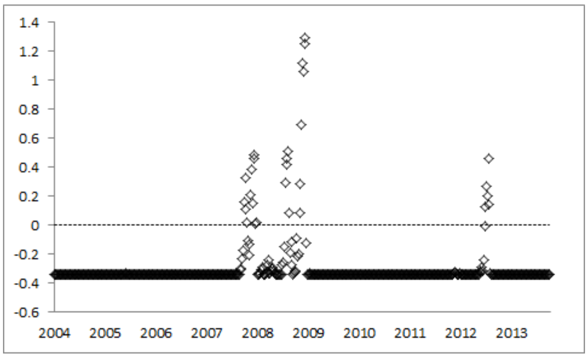
(c) Equity volatility



(d) Yield curve



(e) Risk free rate



(f) Market volatility

Note: Time (in weeks) on the horizontal axis; estimated parameters $(\beta_{0,k} + \beta_{1,k} g_{1,k})$ on the vertical axis.

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