Do the Stock and CDS Markets Price Credit Risk Equally in the Long-run?

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Abstract

In this paper, we examine the existence and stability of the long-run equilibrium relation between the price of credit risk in the stock and CDS markets for a sample of non-financial iTraxx Europe companies during the 2004-2014 period. We show that standard cointegration tests with no breaks frequently fail to detect cointegration. Once we formally account for the breaks in the cointegrating vector, we are able to detect cointegration over the entire sample period for the vast majority of the companies considered. An application of these results to CDS-equity trading shows that the profitability of traditional trading strategies crucially depends on the presence of cointegration and on the stability of the cointegrating vector.

JEL classification: G01, G12, G14

Key words: Credit Default Swaps; Structural Breaks; Cointegration

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1. Introduction

Information on the credit risk of a particular company should be incorporated into the price of its credit-sensitive claims, such as bonds, credit default swaps (CDS) or stocks. This is the primary reason why understanding the interconnectedness between the credit and equity markets became relevant to regulators and market participants. On the one hand, financial regulators have put credit-sensitive markets under increased scrutiny since the onset of the recent global financial crisis. A special focus has been placed on the largely unregulated and opaque CDS market, which has been blamed for fomenting financial instability and creating systemic risk (Cont 2010; Stulz 2010; Augustin et al. 2016). Against this backdrop, it became crucial to determine which of these markets incorporates first the information regarding credit risk (i.e., which of these markets leads in price discovery). On the other hand, market participants began to exploit market inefficiencies in the CDS and equity markets in order to profit from mispricing between the debt and equity of the same underlying reference entity (Yu 2006; Duarte et al. 2007). This trading strategy, popularly known as *capital structure arbitrage* (CSA), exploits short-term deviations but asks that markets ultimately converge in their opinion regarding the credit risk.[1] In either case, drawing inferences on the information revelation and pricing efficiency needs to be based on the prior examination of the existence and stability of the long-run equilibrium relation. Formal analysis of this question, however, was neglected in the previous literature. In this paper, we fill this gap.

If credit risk is priced equally in the stock and CDS markets in the long-run, then these markets should be cointegrated, and the common factor can be considered the implicit efficient price of credit risk. Although the literature on the CDS-equity relation is wide, surprisingly, only a couple of studies incorporate the long-run equilibrium relation in the

[1] In other words, CSA is implicitly based on the assumption that there exists a long-run equilibrium between the stock and CDS markets.

analysis.[2] The vast majority of the studies focus instead on the short-term dynamics and information revelation by investigating lead-lag relations between changes in CDS spreads and stock returns under the vector autoregressive specification (Longstaff et al. 2003; Norden and Weber 2009; Trutwein and Schiereck 2011; Hilscher et al. 2015; Marsh and Wagner 2016; Tolikas and Topaloglou 2017). The long-run equilibrium relation between the stock and CDS markets was taken into account in Forte and Peña (2009), Narayan et al. (2014), Forte and Lovreta (2015) and Kryzanowski et al. (2017). However, these studies as well primarily focus on the short-term dynamics and time variation of the relative market contributions to price discovery while being silent about the nature of the long-run dynamics.

In this paper, contrary to previous research, we focus exclusively on the long-run equilibrium relation between the price of credit risk in the stock and CDS markets and its stability over time. We provide empirical evidence on the long-run dynamics by considering not only the standard Johansen and Engle-Granger cointegration tests but also the econometric techniques of Gregory and Hansen (1996 a,b), Johansen et al. (2000) and Qu (2007) which allow us to formally test the presence of structural breaks in the cointegrating vector. Previous empirical evidence on this issue is rather scarce and limited to the standard cointegrating vector with no breaks. Kryzanowski et al. (2017), for example, estimate weekly vector error correction model (VECM) on a firm-specific basis but do not analyze the presence of cointegration. Narayan et al. (2014) consider panel cointegration but all reported trace statistics point out to the full rank (i.e. two cointegrating vectors within two-dimensional system).[3] Forte and Peña (2009), for the 2001-2003 period, find statistical

[2] This is in contrast with the bond and CDS markets which have been commonly related within the cointegrating framework in the academic literature (Blanco et al., 2005; Zhu, 2006; Baba and Inada, 2009; Norden and Weber, 2009; Forte and Peña, 2009; Coudert and Gex, 2013; Arce *et al.*, 2013).

[3] Narayan *et al.* (2014), however, directly relate stock prices and CDS spreads within the cointegrating framework. Strictly speaking, such a relation is not theoretically grounded in one underlying efficient economic variable. Kryzanowski *et al.* (2017) stress out that from a theoretical point of view the stock and CDS markets can be linearly related through three possible economic variables: unlevered firm's asset value (implied in the stock and CDS markets), equity (observable in the stock and implied in the CDS market), and credit risk (implied in the stock and observable in the CDS market).

evidence of cointegration for 23.5% of their sample of companies at a 5% significance level. Along the same line, Forte and Lovreta (2015) consider a longer time period, 2002-2008, and find evidence of cointegration between the stock and CDS markets for 55.4% of their sample at a 5% significance level. We hypothesize that this relatively low percentage of detected cointegrating relationships might be the result of the presence of structural breaks in the data. Namely, it has been shown in the literature that structural breaks may bias the results of conventional cointegrating tests (Gregory et al. 1996; Kim 2003; Qu 2007). Standard cointegration tests have 'non-cointegration' as the null hypothesis and assume that under an alternative hypothesis, the cointegrating vector is time-invariant. If there is a change in the cointegrating vector, then these tests will not be appropriate; they may falsely fail to reject the null hypothesis and therefore falsely conclude that there is no long-run relationship.

To be able to relate these two markets within the cointegrating framework, we need one homogeneous and comparable measure of credit risk. In the CDS market, credit risk is explicitly traded, and CDS spread (i.e., the fee that the buyer of the credit protection pays to the seller) serves as the market observable proxy for the "pure" credit spread. In the case of the stock market, we follow Forte and Peña (2009), Forte and Lovreta (2015) and Kryzanowski et al. (2017) and use stock market implied credit spreads (ICS) derived by means of the structural credit risk model. As discussed in Forte and Peña (2009), the functional relationship between stock prices and credit spreads is highly non-linear and must be accounted for in the analysis. That is, a cointegrating relationship cannot be theoretically justified if the stock prices instead of ICS are considered.[4] Given that we relate the stock and CDS markets in a dynamic framework, we essentially utilize the structural credit risk model to non-linearly transform stock prices into credit spreads. Consequently, as long as the main parameters of the model remain constant, the main contributor to change in ICS will be

[4] Forte and Peña (2009) provide an intuitive example "*if both equity capital and debt levels double during a given period. Other things being equal, CDS, ... and ICS should exhibit a stable pattern .... Stock prices, on the contrary, will show twice their original value*".

precisely the change in the equity price (Yu 2006; Forte and Peña 2009). In this paper, we utilize the CreditGrades structural credit risk model, considered to be an industry benchmark in quantifying credit risk and implementing capital structure arbitrage (Yu 2006; Duarte et al. 2007; Cao et al. 2011).

We contribute to the existing literature in several ways. First, we provide empirical evidence that the CDS and ICS series are cointegrated over the entire 2004-2014 period for the vast majority of the companies considered. Second, we show that the failure to detect cointegration is largely due to the presence of structural breaks in the cointegrating vector. Utilizing the standard Johansen cointegration test, we find supporting evidence of cointegration for only 31.7% of the sample. Once we allow structural breaks in the parameters of the cointegrating vector using the Johansen et al.'s (2000) procedure, the percentage of companies for which we detect the presence of cointegration rises to 76.2%. Moreover, the 'strong' evidence of cointegration is supported by at least one of the five considered econometric tests for as much as 88.9% of the sample, suggesting that credit risk is priced equally in the stock and CDS markets in the long-run. Third, we provide evidence that the absolute majority of detected breaks falls in the 2007-2008 period, which coincides with the onset of the global financial crisis. However, commonly exogenously imposed break dates in the empirical analysis—June 2007 and the Lehman Brothers collapse in September 2008—are not among the most frequent ones. None of the breaks fall in September 2008, and only 0.6% of the statistically significant structural breaks fall in June 2007. Finally, to provide some recommendations for traders, we study the implications of our results on the capital structure arbitrage trading and provide evidence that the presence of cointegration is the primary requirement for successful trading strategy. We report high annualized Sharpe ratios for companies with cointegrated CDS and ICS spreads as opposed to a low profitability of trading pairs that lack evidence of cointegration. Moreover, we show that the profitability of CDS-equity trading based on traditional trading strategies depends not only on the presence of cointegration but also on the stability of the cointegrating vector. For traditional trading strategies, based on pricing errors, we report higher Sharpe ratios for companies with no breaks in the cointegrating vector. This difference, however, disappears if the trading strategy is based on cointegrating residuals instead.

The remainder of the paper is structured as follows. Section 2 describes the CDS and ICS data. Section 3 presents and applies the econometric methodology of cointegration under the presence of a structural break. Section 4 applies the main results to the capital structure arbitrage trading, and Section 5 concludes.

2. Data Set

2.1 *Credit default swaps*

The single-name CDS represents a type of bilateral insurance contract that transfers the credit risk of an underlying reference entity from the buyer to the seller. The buyer of the protection pays the seller a periodic premium, called a CDS spread, as compensation for protection against the default of the particular reference entity (the premium leg). In the case of default, the contract terminates, and the seller of the protection pays the difference between the par value and the recovery value of the reference obligation to the buyer (the default leg). At the time the contract is initiated, the CDS spread is set so that the present value of the premium leg equals the present value of the default leg. The CDS spread is therefore a directly observable market measure of credit spread. Moreover, not only the CDS market allows credit risk to be explicitly traded but is also shown to be less affected by non-default factors than the bond market (Longstaff et al. 2005).

In this paper, we use a sample of non-financial companies that belong to the iTraxx Europe index, which we track during the period that spans from January 2004 to December 2014. The iTraxx Europe index comprises the most liquid 125 CDS-referencing European investment-grade companies. We exclude all companies in the banking and financial sector due their different capital structure. Additionally, we exclude all companies for which we lack data on either market capitalization or CDS spreads for the overall sample period (for example, acquired or delisted companies). Data on CDS spreads are downloaded from Datastream. For the purposes of this study, we consider only the most liquid Euro-denominated 5-year CDS contracts on senior unsecured debt.

After the initial filtering, we are left with a sample of 75 actively traded names. The final sample is homogeneous—that is, all companies are tracked during the entire 2004-2014 period. In this way, we avoid the possibility of obtaining spurious results due to changes in the sample composition over time. Table 1 reports the main characteristics of the companies in the sample. The average company in the sample has a market capitalization of €23 billion, leverage of 0.54, and a historical equity volatility of 30%. The complete list of companies considered is provided in Appendix A.

<Table 1 about here>

2.2 *Stock market implied credit spreads*

Structural credit risk models provide a theoretical relationship between credit spreads and equity price. This class of models derives from the seminal work of Merton (1974) and is based on the idea that both equity and debt can be considered contingent claims on the underlying driving state variable, i.e., the firm's asset value. Default occurs the first time a firm's asset value reaches the default barrier, defined as the amount of the firm's asset that remains in the case of default. In this paper, we rely on the CreditGrades structural credit risk model, jointly developed by Deutsche Bank, Goldman Sachs, JP Morgan and RiskMetrics Group and commonly used by market participants to quantify credit risk (Yu 2006; Cao et al. 2011).

Under the CreditGrades model, the firm's asset value is assumed to evolve according to the geometric Brownian motion with zero drift:

$$\frac{dV_t}{V_t} = \sigma dW_t \tag{1}$$

where V_t is the firm's asset value at time *t*, σ is the asset volatility, and W_t is the standard Brownian motion. The default barrier is defined as a log-normally distributed random variable and is given by

$$L \times D = \bar{L} D e^{\lambda Z - \lambda^2/2} \tag{2}$$

where L is a random global recovery rate on all liabilities of the firm with mean $\bar{L} = E(L)$ and standard deviation $\lambda^2 = \text{var}\ ln(L)$, Z is a standard normal random variable, and *D* is the firm's debt.

The CreditGrades model provides closed-form solutions for the survival probability and the credit spread. The survival probability up to time *t*, $P(t)$, is given by

$$P(t) = \mathbf{\Phi}\left[-\frac{A_t}{2} + \frac{ln(d)}{A_t}\right] - d\mathbf{\Phi}\left[-\frac{A_t}{2} - \frac{ln(d)}{A_t}\right], \tag{3}$$

where $\mathbf{\Phi}(\cdot)$ is the cumulative normal distribution function, and

$$d = \frac{V_0}{\bar{L}D} e^{\lambda^2},$$

$$A_t^2 = \sigma^2 t + \lambda^2.$$

The credit spread, *c*, that makes the value of a CDS contract with maturity *t* equal to 0 is equal to

$$c = r(1 - R)\frac{1 - P(0) + e^{r\xi}\big(G(t + \xi) - G(\xi)\big)}{P(0) - P(t)e^{-rt} - e^{r\xi}\big(G(t + \xi) - G(\xi)\big)} \tag{4}$$

where *r* is the risk-free interest rate, *R* is the recovery on a specific debt issue that constitutes the underlying asset for the CDS, $\xi = \lambda^2/\sigma^2$, and function *G* is given by

$$G(u) = d^{z+1/2}\mathbf{\Phi}\left[-\frac{ln(d)}{\sigma\sqrt{u}} - z\sigma\sqrt{u}\right] + d^{-z+1/2}\mathbf{\Phi}\left[-\frac{ln(d)}{\sigma\sqrt{u}} + z\sigma\sqrt{u}\right]$$

with $z = \sqrt{1/4 + 2r/\sigma^2}$.

Finally, CreditGrades relates the asset volatility (σ) and equity volatility (σ_S) using the linear approximation of the firm's asset value, $V = S + \bar{L}D$, where S is the market value of equity. This assumption implies that asset volatility can be calculated by applying the gearing ratio, $S/(S + \bar{L}D)$, to the reference equity volatility (σ_S^*). For a detailed description of the CreditGrades model, see Finkelstein et al. (2002).

In a nutshell, we estimate the stock market implied credit spreads (ICS) at daily frequency as the function of a firm's asset value and other variables necessary to specify the model: the global recovery rate, the standard deviation of the global recovery rate, the bond-specific recovery rate, the risk-free rate and asset volatility. The global recovery rate, $\bar{L}$, which actually determines the default barrier, is calibrated to the CDS data so that the sum of squared pricing errors between actual CDS spreads and fitted credit spreads is minimized. For the sample considered, the calibrated mean global recovery rate is found to be 0.58. The standard deviation of the global recovery rate, λ, is set to 0.3, following the suggestion of the CreditGrades Technical Document (Finkelstein et al. 2002). The bond-specific recovery rate is set to 0.4. The proxy chosen for the risk-free rate in the structural model is the swap rate. A firm's debt is defined, following Yu (2006) and Duarte et al. (2007), as the value of total liabilities of the firm. Daily data on market capitalization, 5-year local swap rates and accounting items (short- and long-term liabilities) are downloaded from Datastream.

In this paper, given our goal to study the long-run relation between the price of credit risk in the stock and CDS markets, the input to the model should be an estimate of the long-run volatility. Accordingly, the reference equity volatility is calibrated to match the realized equity volatility for the overall sample period.[5] Our choice to use constant volatility as an

[5] Alternatively, when the other parameters of the model are held fixed, pricing errors could be thought of as deviations of the estimated from implied asset volatility (i.e., the level of asset volatility for which the structural

input in the model is motivated by several reasons. First, any rolling-window historical volatility estimate would introduce "ghost effects" in the ICS time series, thus potentially contaminating the results. Second, it has been shown in the literature that pricing errors decline with the estimation horizon and that estimates based on recent data are inappropriate (Finkelstein et al. 2002; Cao et al. 2011). Third, we disregard the possibility of using implied volatility from equity options as we aim to focus exclusively on the long-run relation between the stock and CDS markets. Therefore, including information from another credit-sensitive market would bias our findings. In addition, Bedendo et al. (2011) study the gap between model and market credit spreads and show that model spreads tend to overreact to movements in the equity option market. They demonstrate that these large gaps tend to be subsequently reabsorbed, showing some type of mean-reverting behavior. Appendix B provides evidence that ICS based on constant volatility estimate clearly dominate any other volatility assumption in explaining the time-series variation of CDS spreads.

Finally, we refrain from any recalibration of other model parameters because this would clearly not be appropriate for the purposes of our study. Recalibration of model parameters to market observable CDS spreads would obviously artificially force cointegration (and contaminate any price discovery) by imputing information from CDS spreads into ICS, but we could make no conclusions regarding the actual existence of the long-run equilibrium between the considered markets over the entire sample period. In contrast, our primary concern is that the main contributor to changes in ICS is the change in equity price and, in the context of this application, we can simply think about the structural model at hand as a non-linear function that translates stock prices into credit spreads.[6] For our choice of model parameters and for the sample of companies considered, the mean CDS

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model recovers the CDS price). Therefore, another valid approach for studying the long-run relationship between the stock and CDS markets would be to use mean implied asset volatility from observed CDS quotes.

[6] Similar arguments are used in Yu (2006) for the purposes of capital structure arbitrage and in Forte and Peña (2009) for the purposes of credit risk discovery in stock, CDS and bond markets.

spread on a cross-sectional basis is equal to 107.29 bp, whereas the mean ICS is slightly lower, 105.43 bp. Appendix A provides the mean CDS spread and the mean ICS estimates on a company-by-company basis.

3. Methodology

The problem with the conventional cointegration tests is that the null hypothesis of non-cointegration may not be rejected when structural shifts are present in the data. In that case, we would falsely conclude that the series in question were not cointegrated. To investigate whether this issue has important implications for defining the long-run relation between the price of credit risk in the stock and CDS markets, we consider several tests that allow the possibility of regime shifts in the cointegrating vector. Specifically, we utilize Gregory and Hansen's (1996 a,b) residual-based test, Johansen et al.'s (2000) cointegration test when structural breaks are present in the deterministic trend, and the non-parametric procedure of Qu (2007). Each test is designed to test for cointegration in the presence of structural breaks. As explained later, these tests treat the issue of the break presence differently, but in a way that enables thorough investigation of long-run relations with a structural break. When applicable, we combine results from different approaches.

We first conduct Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for the presence of unit roots in CDS and ICS series. We use weekly data to minimize market microstructure effects and log-transform data to emphasize the focus on relative pricing in the cointegrating relation. Our sample size, T, is equal to 575 weeks. The ADF unit root test is performed for the three possible alternatives: without constant or trend, with constant and without trend, and with constant and trend. The lag length is selected on the basis of a downward t-test starting from the maximum number of lags, set to 18 in accordance with Schwert's (1989) rule.[7] Likewise, for the PP test, the number of lags of the residual

[7] $l = \left[12(T/100)^{1/4}\right]$, where $[\cdot]$ denotes the integer part.

autocorrelations is set to 18. We exclude all companies for which the null hypothesis of the presence of unit-roots in CDS or ICS series is rejected at the 5% significance level for one of the tests and at least at 10% for the other. In total, we exclude 12 companies that present some evidence of stationarity in at least one of the series. The null hypothesis of non-stationarity for the first differences in the CDS spread and ICS series is rejected for all companies in the sample.

The point of interest in modeling the long-run relation is the time development of the basis i.e., the difference between the ICS and CDS spreads, and its time-series properties. The basis exhibits on average a decreasing pattern over the time period considered. Pricing errors were higher at the beginning of the sample period and lower towards the end for as many as 90.5% of 63 companies with non-stationary CDS-ICS pairs. For illustrative purposes, Figure 1 depicts the time development of the cross-sectional mean of the firm-specific basis for the log-transformed variables. Notably, the mean basis seemingly shows an overall trended divergence, with marked valleys in the 2007-2008 period. As a result, the inclusion of only a constant might not be sufficient for modeling the long-run relation, and we *a priori* do not rule out including the linear trend in the cointegrating equation.[8] We suspect that given the time period we examine, this time development of the basis might be the consequence of common liquidity shocks in the CDS market and their potentially persistent behavior. Bedendo et al. (2011), for example, find that liquidity has a significant impact on the gap between the model and market credit spreads.

<Figure 1 about here>

3.1 *Gregory and Hansen's (1996 a,b) residual-based test*

Gregory and Hansen (1996 a,b) propose a residual-based test for cointegration that allows the possibility of a one-time regime shift in the cointegrating vector. The null

[8] The aim would be to capture the effect of potentially present non-default systematic components that are not explicitly modeled but might have permanent effects on either the CDS market or the stock market.

hypothesis of non-cointegration is tested against the alternative of cointegration in the presence of a possible single regime shift of unknown timing. We examine several forms of structural change in the parameters of the cointegrating vector: the level shift model (C), the level shift with trend model (C/T), the regime shift model (C/S) and the most general model with regime and trend shifts (C/S/T). For the two-variable setting, the considered models are defined as follows:

Model C allows the shift in the intercept of the cointegrating equation:

$$y_{1t} = \mu_1 + \mu_2 d_t(\tau) + \beta y_{2t} + e_t \tag{5.1}$$

Model C/T introduces a time trend in the level shift model:

$$y_{1t} = \mu_1 + \mu_2 d_t(\tau) + \delta t + \beta y_{2t} + e_t \tag{5.2}$$

Model C/S allows the shift in the intercept and the slope:

$$y_{1t} = \mu_1 + \mu_2 d_t(\tau) + \beta_1 y_{2t} + \beta_2 y_{2t} d_t(\tau) + e_t \tag{5.3}$$

Model C/S/T allows the shift in the intercept, the slope and the trend:

$$y_{1t} = \mu_1 + \mu_2 d_t(\tau) + \delta_1 t + \delta_2 t d_t(\tau) + \beta_1 y_{2t} + \beta_2 y_{2t} d_t(\tau) + e_t \tag{5.4}$$

where y_t is a 2×1 vector of the time series of credit spreads; μ_1, β_1 and δ_1 represent the intercept, the slope and the trend coefficient, respectively, before the structural break; μ_2, β_2 and δ_2 are the corresponding changes in the coefficients after the break; and $d_t(\tau)$ is a dummy variable that takes a value of 0 if $t \leq \tau$ and 1 if $t > \tau$.

We compute the ADF test statistic and the Phillips (1987) test statistics, Z_α and Z_t, for each possible break point τ in the interval $([0.15T], [0.85T])$. For the ADF test, the lag length is selected on the basis of a downward t-test. For the Z_α and Z_t test statistics, we follow Gregory and Hansen (1996 a,b) and use the quadratic spectral kernel in combination with the Andrews bandwidth estimator. The statistics of interest for testing the null hypothesis of non-cointegration against the alternatives described in Equations (5.1)-(5.4) is the largest negative value across all computed values:

$$ADF^* = \inf_{hT \leq \tau \leq (1-h)T} ADF(\tau) \tag{6.1}$$

$$Z_\alpha^* = \inf_{hT \leq \tau \leq (1-h)T} Z_\alpha(\tau) \tag{6.2}$$

$$Z_t^* = \inf_{hT \leq \tau \leq (1-h)T} Z_t(\tau) \tag{6.3}$$

The results of Gregory and Hansen's (1996 a,b) residual-based test for the sub-sample of 63 companies with non-stationary CDS and ICS series are presented in Table 2. For 39 companies (62%), all three test statistics (ADF*, Z_α, and Z_t) are statistically significant for at least one of the models (C, C/T, C/S and C/S/T), strongly rejecting the null hypothesis of non-cointegration. The shift in the intercept (model C) is supported by all three test statistics for 36 companies (57.1%), while models C/S and C/T are supported for 27 (42.9%) and 25 (39.7%) companies, respectively. The most general alternative (model C/S/T) is supported by all three test statistics for 19 companies (30.2%). Overall, we find some evidence of cointegration for the vast majority of companies considered. That is, for 53 companies (84.1%), at least one test statistic is statistically significant at 10% level.

<Table 2 about here>

The absolute majority of the estimated break dates fall in the 2007-2008 period but do not coincide with commonly exogenously imposed breakpoints in empirical analyses: June 2007 and Lehman Brothers' collapse in mid-September 2008. When the timing of the structural break under the alternative hypothesis is determined endogenously, only 0.6% of the statistically significant structural breaks fall in June 2007, and none of the breaks falls in September 2008. The majority of the detected breaks (81.2%) fall in the interim period, July 2007 – August 2008. More narrowly, 77.5% of the detected breaks concentrate in the August 2007 – April 2008 period. Only 10.4% of detected breaks fall before June 2007, and only 7.8% fall after September 2008. For illustrative purposes, Figure 2 depicts the cross-sectional mean of the $ADF(\tau)$ statistics over a truncated sample for all models considered. Figure 2 clearly reveals that on average, the smallest test statistics fall during the onset of the global financial crisis. Given that major breaks occur in the middle of the sample period, it seems that the time period considered is suitable for testing the presence of structural breaks in the two markets.[9]

<Figure 2 about here>

If the null hypothesis of non-cointegration is rejected, this does not necessarily imply that there is a break in the cointegrating vector. This is because Gregory and Hansen's (1996 a,b) test subsumes as a special case the standard Engle-Granger (1987) ADF cointegration test with no structural breaks. Therefore, if the conventional ADF test also rejects the null hypothesis of non-cointegration, we cannot conclude that there is a structural break. The results of the ADF cointegration test for none (n), constant (c) and constant and trend (ct) possibilities for the deterministic component are presented in Table 2. The Engle-Granger (1987) test provides little evidence in favor of cointegration: the null hypothesis of non-cointegration is rejected for 12 companies (19%) at a 5% significance level and for 16 companies (25.4%) at a 10% significance level. This result clearly shows that if we did not account for structural breaks in the data, we would falsely conclude that there was no long-run equilibrium relationship between the stock and CDS markets for a substantial number of companies.[10]

3.2 *Johansen et al.'s (2000) test*

Johansen et al. (2000) generalize the multivariate likelihood procedure of Johansen (1988) by admitting structural breaks in the cointegration space. For comparison purposes, we start by applying the standard Johansen cointegration test with no breaks (Johansen 1988, 1991, 1996; Johansen and Juselius 1990) to each non-stationary CDS-ICS pair using the full sample period. The initial cointegrated vector autoregressive model without any breaks is given by the following expression:

[9] It would be difficult to account for breaks that occur at the very beginning or at the very end of the sample period.
[10] Gregory *et al.* (1996) show that the power of the ADF test falls sharply in the presence of a structural break.

$$\Delta y_t = \alpha(\beta' y_{t-1} + \gamma' t) + \mu + \sum_{i=1}^{k-1} \Gamma_i \, \Delta y_{t-i} + \varepsilon_t \qquad (7)$$

where Δ is the first difference operator, y_t is a 2×1 vector of stochastic variables, α and β are $2 \times r$ matrices of full rank, μ is a vector of constants, k is the order of the vector autoregressive model, and ε_t is a vector of i.i.d. error terms.

To model deterministic terms, we start from the most general specification—the linear trend model—and further successively restrict parameters γ and μ.[11] Specifically, we consider the trend, the constant and the model with no deterministic component. The model with trend entering cointegration space restrictedly implies that the constant is present in the cointegrated VAR model. The model with the constant restricted to the cointegration space does not have any deterministic component in the cointegrated VAR model. The model with no deterministic components within the cointegration space has a constant entering the cointegrated VAR model. The number of lags is determined using the general to specific approach starting from the VAR model of order 20. Johansen's trace test is calculated from eigenvalues λ_1 and λ_2, which are involved in maximizing the log-likelihood function of model (7) to estimate cointegrated vectors β. Within our two-dimensional system, Johansen's trace test for the null hypothesis that cointegration does not exist is defined as $-T \sum_{i=1}^{2} ln(1 - \lambda_i)$.

This test shows evidence of cointegration for only 20 companies (31.7%). Detailed results for this sub-sample are presented in Table 3. It is worth noting that for a substantial number of companies, the trend component is found to be statistically significant and is thus included in the cointegration space. As expected, the economic effect of the trend component in the cointegrating relation is small; however, it helps to 'fine-tune' the cointegrating relation. For all those companies, the overall trend component is found to have the same sign,

[11] The quadratic trend model is not considered.

which is in line with the preliminary analysis and indicative of the systematic behavior of pricing errors during the time period considered.

<Table 3 about here>

For the remaining 43 companies, we allow breaks in the deterministic component using the procedure of Johansen et al. (2000). These authors extend the standard VECM, presented in Equation (7), by adding a number of dummy variables to account for structural breaks in the cointegrating space. We consider the possibility of one structural break and consider two models: one with a broken level and the other with a broken trend. The VECM model with one structural break is given by

$$\Delta y_t = \alpha \binom{\beta}{\gamma}' \binom{y_{t-1}}{tE_t} + \mu E_t + \sum_{i=1}^{k-1} \Gamma_i \, \Delta y_{t-i} + \sum_{i=1}^{k} \kappa_i \, D_{t-i} + \varepsilon_t \qquad (8)$$

where $E_t = (E_{1t}, E_{2t})'$ is a vector of dummy variables; $E_{j,t}$ takes a value of 1 if the observation *t* falls in period *j* and 0 otherwise, for $j = 1{,}2$ and the first *k* observations of each sub-sample set to 0; $\mu = (\mu_1, \mu_2)$; $\gamma = (\gamma_1', \gamma_2')'$; D_t is an indicator function that takes a value of 1 if observation *t* is the i^{th} observation in the second period.

The procedure of Johansen et al. (2000) requires that the timing of the break date be known. The break date is first chosen according to the results of Gregory and Hansen’s (1996 a,b) procedure. If the break date appears insignificant, then the points of instability found within the recursively calculated eigenvalues and trace statistics are taken into account. The results of Johansen et al.’s (2000) cointegration test are presented in Table 4. The trace test is used again, but it is now associated with model (8), which requires specific set of critical values provided by Johansen et al. (2000). When cointegration is tested and estimated in the presence of a structural break, a cointegrating relationship is found for 28 companies more. It is clear that without accounting for the presence of a structural break, we would fail to confirm cointegration for a substantial number of companies. Notably, in a number of cases, the result is the cointegration under the change in the parameters of the linear trend. This result could indicate the eventual change in non-default components that have long-term effects on the CDS market and/or the stock market but do not cancel each other out.

<Table 4 about here>

3.3 *Qu's (2007) non-parametric test*

Kim (2003) shows that the failure to detect a cointegrating relationship is in many cases due to segmented cointegration, which is characterized by temporary non-stationary deviations from the long-run relation. This situation might occur when, for example, crisis events temporarily 'switch off' cointegration that prevails in other parts of the sample period. Kim (2003) shows that even a relatively short duration of non-stationary deviations may lead to a failure to detect cointegration. For our dataset, the results of Gregory and Hansen's (1996 a,b) test and Johansen et al.'s (2000) test reveal that the presence of structural changes in the long-run relation between the stock and CDS markets is largely due to the recent global financial crisis. In view of these findings, the time period examined provides a suitable setting for testing the presence of segmented cointegration.

To investigate this issue, we utilize the non-parametric test of Qu (2007). The test is able to reveal whether a cointegrating relationship holds in any or more parts of the sample and assumes that the timing of regime changes is unknown. Therefore, compared to previously applied tests, Qu's (2007) has one additional useful feature: it can detect cointegration if multiple regime changes occur. The null hypothesis of interest is that cointegrating rank r_0 is zero for the full sample (H_0: $r_0=0$) and is tested against the alternative hypothesis that there exist $r>r_0$ cointegrating relationships in some sub-sample, $T_1 \leq t \leq T_2$. We consider the $SupQ^m$ test statistics that assume that the number of structural changes is known and SQ and WQ test statistics that allow an unknown number of regimes. The minimum length of a regime segment relative to the sample size, ε, is set to 0.2.

The $SupQ^m$ test allows *m* structural breaks (i.e., $m+1$ regimes) under the alternative hypothesis. The test statistic is constructed in the following way. For a given partition of the sample, $(T_1, \dots, T_m)$, the $\hat{u}_t$ vector of the OLS residuals is obtained by regressing an *n*-vector of time series, y_t, on the vector of deterministic terms segment by segment. Within each segment, *k*, moment matrices A_k and B_k are constructed:

$$A_k = (T_k - T_{k-1})^{-2} \sum_{t=T_{k-1}+1}^{T_k} \hat{u}_t \, \hat{u}_t'$$

$$B_k = (T_k - T_{k-1})^{-4} \sum_{t=T_{k-1}+1}^{T_k} \left(\sum_{j=T_{k-1}+1}^{t} \hat{u}_j \right) \left(\sum_{j=T_{k-1}+1}^{t} \hat{u}_j \right)'$$

The ratio of the moment matrices, Q_k, is defined as $Q_k = (B_k)^{-1/2} A_k (B_k)^{-1/2}$. Let $\rho_i(Q_k)$ denote the *i*th smallest eigenvalues of Q_k. Then, $\left(\rho_1(Q_k), \dots, \rho_n(Q_k)\right)$ are the ordered solutions of the eigenvalue problem: $|\rho B_k - A_k| = 0$.

For each admissible partition of the sample, the sum of the $n - r_0$ smallest eigenvalues over the $m+1$ segments, i.e., $Q^m(T_1, \dots, T_m) = \sum_{k=1}^{m+1} \sum_{i=1}^{n-r_0} \rho_i(Q_k)$, is calculated. The $SupQ^m$ test statistics are then defined as the supremum over all possible partitions:

$$SupQ^m = \sup_{\Pi \in \Pi_\varepsilon} \sum_{k=1}^{m+1} \sum_{i=1}^{n-r_0} \frac{\rho_i(Q_k)}{100(n - r_0)} \tag{9}$$

with

$$\Pi_\varepsilon = \{(T_1, \dots, T_m); |T_{k+1} - T_k| \geq \varepsilon T, T_1 \geq \varepsilon T, T_m \leq (1-\varepsilon)T\}$$

We consider two additional tests, SQ and WQ, that allow an unknown number of regimes. The SQ and WQ tests are given by

$$WQ = max\left(SupQ^1, \frac{c(\alpha, 1, n - r_0, \varepsilon)}{c(\alpha, 2, n - r_0, \varepsilon)} SupQ^2 \right) \tag{10}$$

$$SQ = SupQ^1 + \frac{c(\alpha, 1, n - r_0, \varepsilon)}{c(\alpha, 2, n - r_0, \varepsilon)} SupQ^2 \quad (11)$$

where $c(\alpha, m, n - r_0, \varepsilon)$ is the critical value of the $SupQ^m$ test at significance level α.

Table 5 presents the results of $SupQ^m$, SQ and WQ tests for the sub-sample of 63 companies with non-stationary CDS and ICS series.[12] We consider three possibilities for the deterministic component: no deterministic terms (none), only a constant term (constant), and a constant and a trend (trend). The SQ and WQ tests for an unknown number of changes reject the null hypothesis of zero cointegrating rank for 31 and 29 companies, respectively, at least at the 10% level. For the $SupQ^m$ test, we allow a maximum of 3 regime changes. The $SupQ^1$ test rejects the null hypothesis for 41 companies (65.1%), at least at the 10% level. The existence of multiple regime changes, however, is detected for 35 companies (55.6%). The $SupQ^2$ test statistic that allows for 2 regime changes is significant for 27 companies, while the $SupQ^3$ test that allows 3 regime changes is significant for 30 companies. That is, for 14 companies, we detect one break; for 5 companies, 2 breaks; and for 30 companies, at least 3 breaks. In total, for 49 companies (77.8%), cointegration holds in one or more parts of the sample, i.e., there exists at least one regime with a cointegrating rank higher than 0.

<Table 5 about here>

For robustness purposes, we consider $SupQ^m$, SQ and WQ tests for the trimming parameter, ε, set to 0.25.[13] In this case, we obtain even stronger evidence in favor of the presence of cointegration in one or more parts of the sample. By way of example, for a higher trimming parameter, the SQ and WQ tests reject the null hypothesis of zero cointegrating rank for 45 and 47 companies, respectively, at least at the 10% level. In total, we find supporting evidence for the presence of cointegration in at least some part of the sample for 52 companies (82.5%). Better results obtained when the minimum length of a regime

[12] We thank Zhongjun Qu for providing the GAUSS code.
[13] Critical values are simulated using the GAUSS code provided by Zhongjun Qu.

segment is augmented, further confirm that cointegration is present in the greater part of the sample. These results are available upon request.

3.4 *Summary*

In this section, we provide a summary of all applied tests. For Gregory and Hansen's (1996 a,b) test, we denote the evidence of cointegration as 'strong' if all three tests statistics (ADF*, Z_α, and Z_t) are found to be significant for at least one of the models. For Qu's (2007) test, we denote the evidence of segmented cointegration as 'strong' if all three tests statistics ($SupQ^m$, SQ and WQ) are found to be significant for at least one of the models. For both Gregory and Hansen's (1996 a,b) test and the Qu (2007) test, the evidence of cointegration is termed as 'weak' if at least one test statistic is significant at the 10% level. Finally, for Johansen's test with no breaks and Johansen et al.'s (2000) cointegration test with structural breaks, the cointegration is denoted as 'strong' if significant at the 5% level.[14]

The evidence of cointegration in its 'strong' form is supported by at least one of the considered tests for as many as 56 companies, that is, 88.9% of the sub-sample of companies with non-stationary CDS and ICS series. On the other hand, all three tests support cointegration for 37 companies (58.7%) at least in the "weak" form. The evidence of breaks in the 'strong' form is supported for 50 companies (79.4%) by at least one of the tests.[15] When these results are compared with the standard Johansen cointegration test, which is able to detect cointegration for 20 companies (31.7%) when applied to the full sample, it becomes clear that allowing for structural breaks is relevant for modeling the long-run equilibrium between the stock and CDS markets.

[14] A summary of all applied tests in a table format is available upon request.
[15] For Gregory and Hansen's (1996 a,b) test, we exclude companies for which the Engle-Granger (1987) test shows evidence of cointegration.

4. Capital structure arbitrage

Capital structure arbitrage (CSA) refers to trading strategies that are based on the relative mispricing between different financial instruments across the capital structure of the same firm. In recent years, due to the rapid development of the CDS market, it has become increasingly popular to exploit mispricing between market CDS spreads and model-implied credit spreads (ICS), that is, to trade on the CDS and equity of the same firm (Yu 2006; Duarte et al. 2007). If CDS spreads are found to be overpriced (underpriced), an arbitrageur will sell (buy) CDS and short sell (buy) equity as a hedge and will eventually profit if the market and model spreads revert to the equilibrium level. The standard CDS-equity trading strategies of Yu (2006) and Duarte et al. (2007) are based on the assumption that the equilibrium is reached when CDS spreads and ICS converge to each other, which means that the theoretical (1 -1) cointegrating vector is explicitly imposed to all companies. Although characterized as a convergence-type strategy, these authors report that convergence actually occurs for only a small fraction of individual trades. Specifically, Yu (2006) reports that out of all initiated trades, fewer than 10% end in convergence.

In this section, as an application of our previous results, we investigate the importance of convergence as an essential condition for successful CDS-equity trading. We study the effect of the existence of the long-run equilibrium and/or the presence of structural breaks in the cointegrating vector on the performance of trading strategies. If there is no cointegration between market and model spreads, pricing errors are non-stationary, and there is no guarantee that convergence will eventually occur. As a result, we would expect underperformance of trading strategies for companies for which we lack evidence of cointegration. The presence of structural breaks in the cointegrating vector, on the other hand, may mask reversion to equilibrium and confound investors. When breaks are present, an increase in pricing errors might just mean convergence to a new equilibrium level. In that case, arbitrageurs might wrongly interpret enter/exit signals, crucially affecting trading performance. To investigate these two issues, we proceed in two steps. First, we compare the performance of the standard trading strategies of Yu (2006) and Duarte et al. (2007) for companies with cointegrated vs. non-cointegrated CDS-ICS pairs. Second, for comparison purposes, we evaluate the performance of CSA trading strategies based not on pricing errors but on equilibrium cointegrating errors, that is, based on the estimated cointegrating vector.

We first resemble the benchmark CSA trading strategy of Yu (2006) and Duarte et al. (2007) based on pricing errors (CSA_{pe}). Specifically, for each observation t, we check whether $CDS_t > (1+h)ICS_t$ or $ICS_t > (1+h)CDS_t$, where the trigger level, h, is assumed to be 0.5. If the market spread (CDS) is substantially higher (lower) than the ICS, an arbitrageur sells (buys) the CDS contract with the notional amount of €1 and short sells (buys) equity as a hedge. The positions are liquidated if the market and model spread converge or if the maximum holding period is reached, whichever occurs first. We consider a holding period of 180 days, but to be consistent with our previous analysis of cointegration, we use weekly frequency.[16] We consider static hedging, and for simplicity, we ignore transaction costs. An initial level of capital for every opened CDS position is set to €0.5. The value of the outstanding CDS position and the equity hedge ratio are calculated according to Yu (2006) and Duarte et al. (2007).[17] We refer interested readers to the original papers for details.

The results for the CSA_{pe}, presented in Panel A of Table 6, allow several observations. First, the relative proportion of the number of trades entered into (N) is substantially higher for companies with non-cointegrated CDS-ICS pairs. For the non-cointegrated sub-sample arbitrageurs that rely on the standard trading rule would see an

[16] We assume that new trade can be opened/closed at weekly intervals. Replicating the analysis at daily frequencies does not alter the main results.
[17] We diverge slightly from original studies and proxy market quotes on an existing CDS contract by interpolating 4-year and 5-year CDS quotes on newly initiated contracts (instead of using only 5-year CDS quotes).

opportunity for trading for as much as 68.4% of the time. This particularly contrasts with companies with a stable cointegrating vector, for which this percentage decreases to 43.8%. Second, the cointegrated sub-sample dominates the non-cointegrated sub-sample in terms of the risk-return tradeoff. When long-run equilibrium is not formally confirmed, the fraction of trades that end in convergence (N_1) is lower, while the fraction of trades with negative holding period returns (N_3) is higher, altogether indicating a higher risk of CSA trading.[18] The mean holding period return (HPR) before transaction costs is statistically significantly lower for the non-cointegrated sub-sample (1.58%) than for the cointegrated sub-sample (2.32%).[19] Finally, we confirm our expectations that the presence of structural breaks in the cointegrating vector negatively affects the performance of standard trading strategies. Although CSA trading on CDS-ICS pairs with shifts in the long-run equilibrium still outperforms the non-cointegrated sub-sample, the presence of breaks leads to a higher percentage of opened arbitrage trades, a higher fraction of trades with a negative HPR, a lower percentage of trades ending in convergence and a lower HPR when compared with trading on CDS-ICS pairs with a stable equilibrium.

<Table 6 about here>

Next, we illustrate the performance of the trading algorithm based on the long-run equilibrium previously estimated in Section 3.2. using either the standard Johansen procedure or Johansen et al.'s (2000) procedure, whichever is appropriate. We define the entry/exit trading trigger on the basis of deviations from the estimated long-run equilibrium. That is, we assume that a new trade is opened when a sufficiently large deviation from the long-run relation is identified. To keep in line with the previous trading structure, we assume that this

[18] The fraction of drawdowns exceeding 20% (N_2) is small for all companies, though slightly higher for the non-cointegrated sub-sample.
[19] t=-8.924***

occurs if $|z_t| > ln(1 + h)$, where z_t is the cointegrating error, and h is the trading trigger, set to 0.5. The trade is closed out when the equilibrium spread levels are reached. Intuitively, we should expect an improved performance of CSA trading strategy based on cointegrated errors (CSA_{ce}). Pricing errors depend on the level of estimated model spreads, in which case model mismeasurement becomes an important issue. This is at least partially solved if cointegrating residuals are instead taken into account.

The results for the CSA_{ce} are presented in Panel B of Table 6. As expected, the CSA_{ce} trading strategy outperforms the CSA_{pe} trading strategy. The frequency of trading is reduced from 51.7% to 23.5%; the percentage of trades that end in convergence is increased from 18.2% to 41.3%; the percentage of trades with negative holding period returns is reduced from 22.3% to 17%; and, finally, the mean HPR is increased from 2.32% to 3.02%, with the difference being statistically significant at the 1% level. Another important finding refers to trading performance of the CDS-ICS pairs with structural breaks. When trades are triggered on the basis of cointegrating residuals, the HPR for this sub-sample of companies increases to 3.10%. In contrast, for companies with a stable cointegrating vector, we find no significant change in the HPR when the CSA_{ce} strategy is applied.

Finally, in line with previous literature, we construct monthly return indices. For each sub-sample of companies, we calculate weekly excess returns on individual trades, form an equally weighted portfolio of all open trades, and finally compound weekly excess returns into monthly frequency. Summary statistics of monthly excess returns are presented in Panel C and D of Table 6. When CDS and ICS spreads are cointegrated, the portfolio of individual trades based on CSA_{pe} produces positively skewed monthly excess returns with a statistically significant mean of 0.26% and an annualized Sharpe ratio of 0.68. In contrast, monthly excess returns for the non-cointegrated portfolio are negatively skewed, with a mean of 0.15% (which is not significant) and an annualized Sharpe ratio of 0.46. Kurtosis is in all cases higher than would correspond to the normal distribution. The mean monthly excess return and Sharpe ratio increase substantially when the trading trigger is based on cointegrating residuals but only for companies with the presence of a break in the cointegrating vector. For companies with a stable long-run equilibrium, however, the mean monthly excess return and the Sharpe ratio are virtually identical for the CSA_{pe} and CSA_{ce} trading strategies.

5. Conclusions

Regulators and market participants are increasingly monitoring pricing efficiency in credit-sensitive markets and their interlinkage. Special attention has been placed on the CDS market, which has been criticized to give rise to financial system instability, and its link to the equity market. In analyzing the CDS-equity relation academic literature has mainly focused on questions related to information revelation in respective markets, detection of where informed traders operate and the profitability of the capital structure arbitrage trading. Answering these questions is essential for efficient allocation of resources and design of adequate regulatory actions aimed at preserving financial stability. However, the underlying question of all: is there a long-run equilibrium relation between the equity and CDS markets?, has been largely neglected in the previous literature. In this paper we fill this gap. We find that such a relation does exist in the majority of the cases but only if structural breaks are accounted for.

In the presence of structural breaks, the standard cointegration tests might fail to detect a cointegrating relationship (Gregory et al. 1996; Kim 2003; Qu 2007). Structural breaks may 'switch off' cointegration or simply move the cointegrating relationship to another level, a situation that might arise, for example, in times of economic crisis. In this paper, we test the existence and structural stability of the long-run relation between the price of credit risk in the stock and CDS markets for a sample of non-financial iTraxx Europe companies during the 2004-2014 period. We utilize not only the standard Johansen and Engle-Granger cointegration tests but also the econometric techniques of Gregory and Hansen (1996 a,b), Johansen et al. (2000) and Qu (2007) to formally test for cointegration in the presence of structural breaks.

Our results allow several conclusions. First, we find clear evidence of a long-run equilibrium between the price of credit risk in the stock and CDS markets for the entire 2004-2014 period. Second, we show the importance of accounting for structural breaks in the cointegrating relationship between the considered markets. Empirical evidence based on standard cointegration tests is not as supportive as one would expect. The standard Johansen cointegration test detects cointegration for 31.7% of the sample. However, once we account for the breaks in the cointegrating vector, we find empirical evidence that the stock and CDS markets do price credit risk equally in the long-run for a vast majority of the companies considered. Third, we show that major break dates fall between August 2007 and April 2008 but do not coincide with commonly exogenously imposed break dates in the empirical analysis. Fourth, we study the implications of our results for capital structure arbitrage trading. We show that CDS-ICS pairs that are characterized with a long-run equilibrium yield a higher return with less risk. The presence of structural breaks in the cointegrated vector, however, negatively affects the performance of standard trading strategies based on pricing errors.

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Table 1. Main characteristics of the companies in the sample

	Mean	Median	St. Dev	Min	Max
MC in m €	23,814.29	15,248.12	24,213.77	3,051.99	130,792.57
Leverage	0.54	0.53	0.14	0.28	0.87
Equity Volatility	0.30	0.29	0.06	0.19	0.44

This table reports the main descriptive statistics on a cross-sectional basis for the initial set of 75 non-financial companies within the European region. MC refers to market capitalization in million euros. Equity volatility is defined as the unconditional historical volatility, calculated as the annualized standard deviation of the continuously compounded returns on equity. Leverage is defined as the ratio of the book value of total liabilities to the proxy for the market value of the firm (i.e., sum of the market value of equity and the book value of total liabilities).

Table 2. Gregory and Hansen's (1996 a,b) residual-based test

comp	ADF*				Z_α*				Z_t*				ADF		
	C	C/T	C/S	C/S/T	C	C/T	C/S	C/S/T	C	C/T	C/S	C/S/T	n	c	ct
1	-5.294 ***	-5.934 ***	-5.249 **	-6.620 ***	-43.935 **	-57.396 ***	-42.905 *	-59.023 **	-4.667 **	-5.389 **	-4.612	-5.473 *	-1.457	-1.435	-1.756
2	-4.768 **	-4.495	-4.676	-4.510	-35.126	-32.427	-35.576	-33.856	-4.171	-3.923	-4.242	-4.018	-1.412	-1.659	-0.570
3	-4.856 **	-5.349 **	-4.827 *	-5.405 *	-41.636 **	-46.969 *	-41.797	-46.887	-4.598 *	-4.856 *	-4.609	-4.862	-1.422	-1.463	-0.901
4	-4.609 *	-5.085 **	-4.445	-5.212	-38.267 *	-48.405 **	-36.443	-50.092	-4.361 *	-4.991 **	-4.240	-5.065	-1.361	-1.774	-2.145
5	-5.405 ***	-5.580 ***	-5.211 **	-5.951 **	-47.171 **	-49.933 **	-46.926 *	-51.885	-4.868 **	-5.031 **	-4.840 *	-5.126	-1.651	-1.679	-0.780
8	-4.866 **	-4.960 *	-5.021 **	-4.927	-28.776	-40.181	-34.324	-40.008	-3.817	-4.635	-4.167	-4.609	-1.160	-1.624	-2.991
9	-4.258	-4.440	-4.180	-4.760	-25.836	-29.283	-30.035	-44.758	-3.612	-3.857	-3.921	-4.815	-1.214	-1.427	-1.595
10	-7.156 ***	-7.643 ***	-7.632 ***	-7.598 ***	-91.636 ***	-88.354 ***	-92.253 ***	-89.420 ***	-7.003 ***	-6.856 ***	-6.997 ***	-6.877 ***	-3.580 ***	-3.444 **	-3.443
11	-6.243 ***	-6.508 ***	-5.670 ***	-5.922 **	-53.241 ***	-58.855 ***	-48.799 **	-54.031 *	-5.181 ***	-5.509 ***	-4.963 **	-5.261 *	-1.777	-2.147	-2.006
12	-4.830 **	-4.644	-4.584	-4.876	-38.677 *	-35.594	-42.971 *	-38.987	-4.420 *	-4.166	-4.644	-4.371	-1.644	-2.583	-3.247
14	-4.429 *	-4.763 *	-6.345 ***	-6.494 ***	-38.723 *	-41.930	-69.233 ***	-70.782 ***	-4.548 *	-4.647	-5.977 ***	-6.014 **	-1.688	-1.574	-2.581
15	-5.654 ***	-5.689 ***	-5.870 ***	-5.864 **	-54.741 ***	-54.731 **	-54.627 **	-54.657 *	-5.309 ***	-5.307 **	-5.298 **	-5.299 *	-2.422	-2.459	-3.386
16	-4.992 **	-4.975 *	-5.534 ***	-5.316 *	-52.765 ***	-50.741 **	-59.273 ***	-56.553 *	-5.189 ***	-5.078 **	-5.514 ***	-5.375 *	-1.152	-1.629	-2.220
17	-4.101	-5.024 **	-4.241	-4.961	-27.171	-45.893 *	-28.744	-43.727	-3.699	-4.854 *	-3.808	-4.736	-2.028	-2.246	-2.206
18	-4.363 *	-4.178	-5.059 **	-4.859	-39.860 *	-37.272	-53.089 **	-48.665	-4.453 *	-4.286	-5.160 **	-4.885	-0.482	-1.365	-2.320
19	-5.054 **	-5.368 **	-5.122 **	-5.424 *	-56.532 ***	-68.980 ***	-59.706 ***	-69.284 **	-5.347 ***	-5.957 ***	-5.504 ***	-5.970 **	-2.404	-2.372	-2.566
20	-5.331 ***	-5.382 **	-6.255 ***	-6.245 ***	-49.531 **	-53.470 **	-91.675 ***	-91.122 ***	-5.053 **	-5.273 **	-6.941 ***	-6.914 ***	-3.457 ***	-3.631 **	-3.406
21	-4.017	-3.834	-4.061	-4.146	-35.685	-35.241	-35.092	-35.098	-4.162	-4.130	-4.122	-4.122	-1.035	-1.761	-3.886 **
22	-4.785 **	-5.674 ***	-4.652	-5.723 **	-32.603	-44.825 *	-32.307	-47.053	-3.956	-4.734 *	-3.934	-4.847	-1.909	-1.703	-2.011
23	-4.908 **	-5.506 ***	-4.840 *	-5.502 **	-42.039 **	-52.503 **	-41.224	-52.269	-4.659 **	-5.313 **	-4.589	-5.227	-2.232	-1.840	-2.511
24	-4.189	-3.957	-4.395	-4.454	-30.694	-28.160	-32.731	-34.876	-4.034	-3.720	-4.082	-4.167	-1.850	-3.238 *	-2.472
25	-6.034 ***	-6.426 ***	-6.626 ***	-6.662 ***	-50.554 ***	-56.606 **	-57.568 ***	-58.512 *	-5.086 **	-5.372 **	-5.413 **	-5.459 *	-0.566	-2.078	-2.468
26	-4.799 **	-5.023 **	-5.664 ***	-5.098	-47.130 **	-54.451 **	-57.041 **	-58.190 *	-4.867 **	-5.264 **	-5.389 **	-5.453 *	-1.930	-2.348	-2.562
27	-5.490 ***	-4.890 *	-5.537 ***	-5.070	-48.163 **	-41.084	-49.564 **	-45.243	-4.964 **	-4.484	-5.043 **	-4.674	-1.554	-2.451	-2.665
28	-4.655 **	-4.647	-4.700 *	-5.036	-36.056	-46.172 *	-38.170	-49.895	-4.356 *	-4.870 *	-4.455	-5.060	-2.535 *	-2.834	-2.785
29	-4.958 **	-4.609	-5.086 **	-4.944	-34.230	-30.721	-39.446	-36.549	-4.130	-3.938	-4.433	-4.253	0.451	-1.611	-3.470
31	-4.663 **	-4.440	-4.133	-4.296	-37.937 *	-35.014	-33.923	-39.695	-4.452 *	-4.233	-4.103	-4.501	-2.060	-2.083	-2.609
34	-4.629 **	-4.488	-4.648	-4.732	-33.445	-33.734	-34.779	-34.809	-4.165	-4.184	-4.240	-4.242	-0.318	-2.329	-2.357
35	-5.357 ***	-5.403 **	-5.589 ***	-5.695 **	-47.221 **	-48.558 **	-54.078 **	-54.666 *	-4.913 **	-4.926 *	-5.234 **	-5.280 *	-0.887	-2.149	-2.371
36	-4.033	-4.116	-3.943	-4.202	-28.641	-31.589	-30.152	-31.927	-3.747	-3.970	-3.849	-3.987	-1.176	-3.293 *	-4.155 **
37	-4.484 *	-4.552	-4.723 *	-4.655	-30.340	-32.535	-31.491	-33.122	-3.890	-4.040	-3.966	-4.077	-3.247 **	-4.332 ***	-5.373 ***
38	-4.761 **	-4.682	-4.657	-4.722	-40.976 **	-40.698	-42.229 *	-43.120	-4.557 *	-4.520	-4.634	-4.664	-3.906 ***	-3.830 **	-3.955 **
39	-4.002	-4.186	-3.836	-5.166	-35.478	-39.296	-39.182	-53.362 *	-3.997	-4.268	-4.207	-5.067	-1.292	-1.469	-1.641
41	-5.265 ***	-4.931 *	-5.133 **	-5.214	-55.260 ***	-54.810 **	-58.679 ***	-59.765 **	-5.317 ***	-5.318 **	-5.473 ***	-5.560 **	-2.068	-2.067	-4.190 **
42	-4.723 **	-5.099 **	-5.160 **	-5.322 *	-33.337	-34.741	-40.283	-36.819	-4.039	-4.130	-4.410	-4.189	-1.725	-1.688	-3.162
43	-6.145 ***	-5.714 ***	-6.104 ***	-5.715 **	-50.226 ***	-52.147 **	-50.828 **	-52.179	-5.686 ***	-5.564 ***	-5.709 ***	-5.753 **	-0.249	-2.385	-4.169 **

Table 2. Gregory and Hansen's (1996 a,b) residual-based test (cont.)

comp	ADF*				Z_α*				Z_t*				ADF		
	C	C/T	C/S	C/S/T	C	C/T	C/S	C/S/T	C	C/T	C/S	C/S/T	n	c	ct
44	-4.587 *	-5.246 **	-4.580	-5.542 **	-40.658 **	-55.063 **	-40.258	-54.190 *	-4.498 *	-5.307 **	-4.474	-5.267 *	-2.198	-2.006	-2.319
45	-4.757 **	-4.496	-5.128 **	-4.900	-43.655 **	-44.406 *	-42.832 *	-40.450	-4.670 **	-4.624	-4.595	-4.385	-1.416	-1.341	-1.540
47	-3.078	-3.718	-3.118	-4.125	-17.542	-34.046	-17.123	-33.371	-2.952	-4.168	-2.912	-4.106	-1.192	-2.362	-3.799 **
49	-6.285 ***	-6.602 ***	-6.253 ***	-6.598 ***	-65.093 ***	-67.279 ***	-63.101 ***	-67.494 **	-5.737 ***	-5.896 ***	-5.696 ***	-5.897 **	-1.544	-1.943	-3.806 **
50	-2.706	-3.190	-3.315	-3.512	-12.886	-17.412	-19.191	-22.406	-2.562	-2.961	-3.188	-3.317	-1.500	-1.405	-2.667
51	-4.921 **	-4.611	-4.519	-4.514	-38.594 *	-35.531	-37.211	-35.358	-4.353 *	-4.050	-4.256	-4.046	-1.615	-1.649	-1.648
52	-3.856	-4.017	-3.923	-3.853	-27.764	-26.193	-26.721	-34.265	-3.735	-3.546	-3.622	-3.850	-1.137	-2.106	-1.951
54	-4.975 **	-5.108 **	-4.865 *	-5.548 **	-53.546 ***	-61.856 ***	-52.648 **	-76.727 ***	-5.216 ***	-5.658 ***	-5.166 **	-6.318 ***	-2.022	-3.079 *	-2.650
55	-3.608	-3.657	-5.528 ***	-5.524 **	-36.372 *	-38.012	-78.855 ***	-77.989 ***	-4.309	-4.401	-6.429 ***	-6.398 ***	-1.253	-2.008	-2.503
56	-5.071 **	-5.184 **	-5.407 **	-5.726 **	-46.648 **	-45.607 *	-54.970 **	-60.169 **	-4.820 **	-4.748 *	-5.158 **	-5.453 *	-0.595	-1.779	-2.015
57	-5.268 ***	-6.443 ***	-5.159 **	-5.646 **	-54.541 ***	-61.858 ***	-51.982 **	-60.501 **	-5.220 ***	-5.592 ***	-5.098 **	-5.528 **	-1.561	-3.054 *	-2.677
59	-4.391 *	-4.508	-4.346	-4.415	-25.789	-29.389	-49.884 **	-49.964	-3.836	-4.059	-5.048 **	-5.058	-4.597 ***	-4.086 ***	-4.153 **
60	-5.048 **	-5.847 ***	-4.988 **	-5.740 **	-51.023 ***	-66.447 ***	-51.540 **	-70.010 ***	-4.973 **	-5.816 ***	-5.008 **	-6.007 **	-1.380	-2.591	-2.310
61	-5.258 ***	-4.691	-5.280 **	-4.718	-36.569 *	-31.605	-36.884	-34.043	-4.268	-3.987	-4.287	-4.151	-1.388	-1.517	-1.312
62	-4.817 **	-5.041 **	-4.851 *	-4.974	-38.800 *	-38.344	-38.846	-38.520	-4.465 *	-4.415	-4.455	-4.424	-1.378	-1.374	-1.153
63	-3.194	-3.654	-3.158	-4.949	-21.755	-25.090	-19.224	-45.838	-3.124	-3.434	-2.893	-4.774	-1.672	-1.472	-1.598
64	-5.852 ***	-5.673 ***	-5.680 ***	-5.643 **	-47.409 **	-44.888 *	-44.660 *	-44.604	-4.909 **	-4.778 *	-4.769 *	-4.763	-1.571	-0.708	-1.681
65	-4.849 **	-5.235 **	-5.019 **	-5.573 **	-45.008 **	-49.974 **	-45.594 *	-56.477 *	-4.927 **	-5.202 **	-4.877 *	-5.416 *	-1.405	-1.425	-1.788
66	-5.991 ***	-5.994 ***	-6.018 ***	-6.013 **	-39.024 *	-38.319	-37.576	-36.875	-4.440 *	-4.399	-4.361	-4.321	-1.742	-1.785	-2.132
67	-4.291	-5.369 **	-4.664	-5.789 **	-33.254	-33.586	-49.798 **	-48.501	-4.135	-4.137	-5.057 **	-4.950	-2.043	-1.914	-2.348
68	-5.764 ***	-5.754 ***	-5.759 ***	-5.746 **	-54.528 ***	-58.604 ***	-52.243 **	-56.063 *	-5.152 ***	-5.377 **	-5.040 **	-5.250 *	-1.052	-2.171	-4.970 ***
69	-5.206 ***	-5.047 **	-4.638	-5.063	-34.895	-35.417	-36.370	-40.234	-4.319	-4.273	-4.409	-4.525	-1.895	-1.893	-1.867
70	-4.213	-4.639	-4.125	-5.521 **	-36.977 *	-44.817 *	-34.973	-54.031 *	-4.196	-4.696	-4.076	-5.230	0.492	-2.202	-3.218
72	-2.591	-4.617	-3.513	-4.718	-14.554	-38.263	-26.757	-44.830	-2.616	-4.425	-3.578	-4.798	-2.132	-2.105	-3.144
73	-4.273	-3.985	-4.918 *	-4.304	-31.824	-28.980	-38.331	-33.950	-3.978	-3.670	-4.322	-4.005	-1.433	-1.417	-0.737
74	-4.108	-3.870	-4.181	-3.864	-35.735	-34.368	-35.806	-35.828	-4.192	-4.144	-4.207	-4.237	-1.728	-2.592	-3.315
75	-5.460 ***	-5.502 ***	-5.480 ***	-5.871 **	-45.638 **	-42.667	-47.105 **	-53.727 *	-4.818 **	-4.652	-4.897 *	-5.179	-1.101	-1.702	-3.390

This table reports the results from Gregory and Hansen's (1996 a,b) residual-based test for the sub-sample of 63 companies. Models for structural change in parameters of the cointegrating vector, C, C/T, C/S and C/S/T, are defined in Equations (5.1)-(5.4), respectively. ADF*, Z_α^*, and Z_t^* are test statistics defined in Equations (6.1)-(6.3), respectively. The trimming parameter is set to 15%. ADF is the standard Engle-Granger (1987) ADF test, performed for the three possible alternatives: without constant or trend (n), with constant and without trend (c), and with constant and trend (ct). For the ADF and ADF* test, the lag length is selected on the basis of a downward t-test. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3. Standard Johansen cointegration test

Comp	Hypothesis	Eigenvalue	Trace test	*p*-value	Deter. Comp.	lags VAR	Cointegrated vector
10	$H_0: r=0$	0.050	32.01	**0.01**	trend	17	$ics - 1.56cds + 0.003trend$
	$H_0: r=1$	0.006	3.23	0.84			(-19.87) (13.61)
12	$H_0: r=0$	0.038	26.98	**0.03**	trend	19	$ics - 0.50cds + 0.002trend$
	$H_0: r=1$	0.010	5.56	0.52			(-5.45) (10.15)
14	$H_0: r=0$	0.039	27.57	**0.03**	trend	11	$ics - 0.36cds + 0.003trend$
	$H_0: r=1$	0.009	5.08	0.59			(-12.08) (15.72)
15	$H_0: r=0$	0.031	23.64	**0.09**	trend	15	$ics - 0.64cds + 0.001trend$
	$H_0: r=1$	0.010	5.77	0.50			(-9.97) (5.38)
17	$H_0: r=0$	0.031	19.87	**0.01**	none	19	$ics - 0.91cds$
	$H_0: r=1$	0.004	2.14	0.14			(-7.92)
19	$H_0: r=0$	0.028	21.47	**0.03**	const.	15	$ics - 1.97cds + 3.8$
	$H_0: r=1$	0.010	5.81	0.21			(-4.65) (2.33)
21	$H_0: r=0$	0.031	22.29	**0.02**	const.	19	$ics - 0.52cds - 1.81$
	$H_0: r=1$	0.008	4.59	0.34			(-4.03) (−3.62)
24	$H_0: r=0$	0.038	27.23	**0.03**	trend	15	$ics - 0.53cds + 0.003trend$
	$H_0: r=1$	0.010	5.48	0.54			(-5.92) (4.18)
35	$H_0: r=0$	0.035	24.93	0.06	trend	8	$ics - 0.57cds + 0.001trend$
	$H_0: r=1$	0.008	4.47	0.68			(-13.03) (8.58)
37	$H_0: r=0$	0.031	21.13	**0.01**	none	19	$ics - 0.91cds$
	$H_0: r=1$	0.006	3.15	0.07			(-9.81)
38	$H_0: r=0$	0.034	23.12	**0.02**	const.	18	$ics - 0.76cds - 1.39$
	$H_0: r=1$	0.007	3.90	0.44			(-10.02) (−3.51)
43	$H_0: r=0$	0.056	36.59	**0.00**	trend	19	$ics - 0.66cds + 0.001trend$
	$H_0: r=1$	0.008	4.54	0.67			(-13.63) (3.80)
45	$H_0: r=0$	0.043	28.83	**0.02**	trend	11	$ics - 0.38cds + 0.003trend$
	$H_0: r=1$	0.007	4.08	0.73			(-7.12) (11.75)
47	$H_0: r=0$	0.028	18.36	**0.09**	const.	17	$ics - 1.58cds + 2.59$
	$H_0: r=1$	0.004	2.31	0.72			(-5.94) (2.34)
59	$H_0: r=0$	0.039	26.21	**0.00**	none	13	$ics - 0.98cds$
	$H_0: r=1$	0.007	3.97	0.05			(-10.76)
60	$H_0: r=0$	0.035	22.76	**0.02**	const.	16	$ics - 0.35cds - 3.67$
	$H_0: r=1$	0.006	3.12	0.57			(-12.10) (−24.15)
62	$H_0: r=0$	0.035	21.52	**0.03**	const.	17	$ics - 0.72cds - 1.63$
	$H_0: r=1$	0.003	1.89	0.80			(-15.17) (−6.87)
66	$H_0: r=0$	0.060	38.05	**0.00**	trend	18	$ics - 0.96cds + 0.004trend$
	$H_0: r=1$	0.007	3.70	0.78			(-9.67) (15.54)
67	$H_0: r=0$	0.064	41.10	**0.00**	trend	19	$ics - 2.52cds + 0.009trend$
	$H_0: r=1$	0.008	4.38	0.69			(-6.67) (5.94)
69	$H_0: r=0$	0.044	29.48	**0.02**	trend	19	$ics - 0.80cds + 0.003trend$
	$H_0: r=1$	0.008	4.47	0.68			(-15.04) (14.41)

This table reports the results of the standard Johansen's trace test for the sub-sample of 20 companies for which the test shows evidence of cointegration. The number of lags is determined using the general to specific approach starting from the VAR model of order 20.

Table 4. Johansen *et al.'s* (2000) cointegration test

Comp	Eigenvalue	Trace test	*p*-value	Deter. Comp.	lags VAR	Break date (τ)	Cointegrated vector
1	0.048	38.61	**0.03**	trend	19	30/05/2007	$ics - 0.97cds - 0.004trend(t \ge \tau) + 0.002trend$
	0.020	11.25	0.38				(-9.34) (–2.33) (1.13)
3	0.050	41.89	**0.01**	trend	17	13/02/2008	$ics - 0.86cds - 0.006trend(t \ge \tau) + 0.008trend$
	0.023	13.20	0.26				(-5.53) (–5.49) (7.85)
4	0.060	43.08	**0.01**	trend	17	12/12/2007	$ics - 2.69cds - 0.015trend(t \ge \tau) + 0.01trend$
	0.015	8.58	0.66				(-5.69) (–2.47) (1.87)
5	0.055	40.05	**0.02**	trend	19	10/10/2007	$ics - 1.06cds - 0.004trend(t \ge \tau) + 0.003trend$
	0.015	8.65	0.64				(-8.34) (–2.17) (2.07)
8	0.055	39.64	**0.02**	trend	15	25/08/2010	$ics - 0.33cds + 0.001trend(t \ge \tau) + 0.002trend$
	0.015	8.21	0.67				(-10.29) (2.21) (4.27)
11	0.026	24.99	**0.07**	const.	17	25/04/2007	$ics - 0.86cds + 0.48(t \ge \tau) - 1.094$
	0.019	10.46	0.12				(-9.38) (2.90) (–3.83)
16	0.038	26.57	**0.05**	const.	11	27/05/2009	$ics - 0.51cds + 1.23(t \ge \tau) - 2.15$
	0.009	4.94	0.64				(-2.91) (5.10) (–3.74)
22	0.046	39.37	**0.03**	trend	14	02/01/2008	$ics - 0.96cds - 0.010trend(t \ge \tau) + 0.008trend$
	0.023	13.06	0.27				(-6.43) (–5.58) (4.64)
23	0.035	31.94	**0.01**	const.	15	15/08/2007	$ics - 0.51cds + 0.63(t \ge \tau) - 3.14$
	0.021	12.08	0.06				(-8.75) (4.79) (–17.46)
25	0.038	26.84	**0.04**	const.	19	05/09/2007	$ics - 0.74cds + 0.79(t \ge \tau) - 2.23$
	0.028	5.37	0.56				(-13.38) (6.27) (–11.01)
26	0.038	32.99	**0.01**	const.	19	01/08/2007	$ics - 1.72cds + 1.60(t \ge \tau) + 1.88$
	0.020	11.44	0.08				(-5.90) (4.73) (2.01)
29	0.046	37.63	**0.04**	trend	17	02/04/2008	$ics - 0.69cds + 0.004trend(t \ge \tau) + 0.007trend$
	0.020	11.40	0.40				(-4.98) (2.75) (5.39)
31	0.073	54.31	**0.00**	trend	16	28/03/2007	$ics - 0.61cds - 0.008trend(t \ge \tau) + 0.007trend$
	0.021	11.67	0.33				(-7.86) (–4.90) (4.77)
34	0.053	32.66	**0.01**	const.	14	06/06/2007	$ics - 0.91cds + 1.04(t \ge \tau) - 1.33$
	0.004	2.23	0.94				(-11.37) (9.65) (–3.85)
39	0.044	36.14	**0.05**	trend	19	16/05/2007	$ics - 0.46cds - 0.004trend(t \ge \tau) + 0.003trend$
	0.020	10.96	0.40				(-7.42) (–2.81) (2.02)
44	0.036	25.01	**0.07**	const.	14	10/10/2007	$ics - 2.313cds + 2.67(t \ge \tau) + 4.00$
	0.008	4.53	0.68				(-6.32) (5.02) (2.93)
49	0.045	36.65	**0.00**	const.	12	10/10/2007	$ics - 0.83cds + 1.34(t \ge \tau) - 2.31$
	0.019	10.95	0.10				(-10.92) (6.83) (–8.73)
51	0.054	39.28	**0.00**	const.	11	09/05/2007	$ics - 0.81cds + 1.10(t \ge \tau) - 2.04$
	0.014	8.24	0.25				(-11.47) (7.18) (–7.77)
54	0.050	39.91	**0.02**	trend	17	02/01/2008	$ics - 0.92cds - 0.013trend(t \ge \tau) + 0.009trend$
	0.020	11.52	0.38				(-6.82) (–10.09) (8.39)
55	0.033	31.02	**0.01**	const.	19	11/04/2007	$ics - 0.32cds + 0.314(t \ge \tau) - 3.37$
	0.022	12.34	0.06				(-2.13) (2.00) (–5.53)
56	0.033	34.26	**0.09**	trend	15	29/08/2007	$ics - 0.22cds - 0.004trend(t \ge \tau) + 0.005trend$
	0.028	15.78	0.12				(-2.40) (–3.23) (3.94)
57	0.042	29.57	**0.02**	const.	14	03/10/2007	$ics - 1.64cds + 2.32(t \ge \tau) + 0.69$
	0.010	5.53	0.54				(-17.32) (7.09) (1.07)
63	0.044	37.32	**0.05**	trend	14	19/03/2008	$ics - 0.28cds - 0.004trend(t \ge \tau) + 0.002trend$
	0.021	11.97	0.35				(-3.08) (–3.86) (2.10)
64	0.063	40.97	**0.00**	const.	11	30/05/2007	$ics - 1.39cds + 2.67(t \ge \tau) - 0.48$
	0.083	4.40	0.69				(-7.22) (7.98) (–0.88)
65	0.042	37.62	**0.04**	trend	19	07/11/2007	$ics - 1.15cds - 0.004trend(t \ge \tau) + 0.003trend$
	0.025	13.81	0.22				(-7.34) (–2.01) (1.65)
68	0.027	25.60	**0.06**	const.	16	05/09/2007	$ics - 1.21cds + 1.61(t \ge \tau) - 0.31$
	0.018	10.29	0.13				(-5.75) (4.00) (–0.38)
70	0.047	38.99	**0.03**	trend	14	02/01/2008	$ics - 0.62cds - 0.017trend(t \ge \tau) + 0.015trend$
	0.021	11.83	0.36				(-3.09) (–7.96) (7.40)
75	0.057	36.03	**0.00**	const.	19	10/10/2007	$ics - 1.39cds + 1.98(t \ge \tau) + 0.27$
	0.006	3.59	0.80				(-9.93) (9.65 (0.52)

This table reports the results of Johansen *et al.'s* (2000) cointegration test for the sub-sample of 26 companies for which the test shows evidence of cointegration after accounting for structural breaks. "Const.' refers to a model with a broken level, and 'trend' refers to a model with a broken trend. The number of lags is determined using the general to specific approach starting from the VAR model of order 20.

Table 5. SupQ^{m}, SQ and WQ test

comp	none				constant				trend			
	SupQ^{m}	*m*	*SQ*	*WQ*	SupQ^{m}	*m*	*SQ*	*WQ*	SupQ^{m}	*m*	*SQ*	*WQ*
1	4.462 *	3	4.483	2.690	2.451	1	5.176	2.724	7.328	1	14.279	7.328
2	3.859 *	2	5.101	2.572	2.562	1	5.384	2.822	14.664 *	3	12.750	6.573
3	1.237	1	2.866	1.629	2.606	1	5.102	2.606	16.093 **	3	14.642	7.800
4	1.700	1	3.678	1.978	2.046	1	3.961	2.046	6.371	1	12.217	6.371
5	4.572 *	3	4.945	2.653	1.904	1	4.437	2.534	5.127	1	10.877	5.750
8	1.130	1	2.636	1.506	2.032	1	4.635	2.603	8.221 *	1	15.465 *	8.221
9	7.233 ***	3	8.115 ***	4.547 ***	9.143 **	3	10.317 **	5.482 **	17.708 **	3	18.395 **	9.868 **
10	2.322	1	4.485	2.322	3.890	1	7.242	3.890	21.803 ***	3	23.794 ***	11.952 ***
11	3.942 **	1	5.913 *	3.942 *	2.200	1	4.454	2.254	14.918 *	3	14.294	7.446
12	2.905 *	1	5.320	2.905	2.074	1	4.028	2.074	15.456 *	3	15.839 *	8.667 *
14	1.529	1	3.934	2.405	2.864	1	5.330	2.864	19.818 ***	3	18.591 **	10.278 **
15	3.201 **	1	4.973	3.201	2.643	1	4.736	2.643	7.650	1	13.392	7.650
16	1.932	1	3.992	2.060	1.753	1	4.681	2.928	14.501 *	3	12.786	6.796
17	2.860 *	1	4.756	2.860	3.606	1	6.349	3.606	8.109 *	1	15.609 *	8.109
18	1.940	1	4.157	2.218	11.318 ***	3	12.602 ***	6.706 ***	20.695 ***	3	18.500 **	10.060 **
19	0.939	1	2.128	1.189	2.600	1	5.187	2.600	8.376 *	1	15.515 *	8.376
20	2.204	1	4.063	2.204	10.370 ***	3	9.146 **	6.693 ***	17.775 **	3	14.295	8.575 *
21	2.239	1	3.748	2.239	2.926	1	5.834	2.926	5.426	1	10.509	5.426
22	4.963 **	3	6.287 *	3.421 *	2.774	1	5.671	2.896	14.581 *	3	13.787	7.680
23	2.803 *	1	4.599	2.803	2.511	1	4.796	2.511	4.810	1	9.270	4.810
24	5.086 **	3	6.487 *	3.510 *	2.022	1	4.945	2.922	7.936 *	1	15.130	7.936
25	1.437	1	2.724	1.437	2.239	1	4.595	2.356	10.050 **	1	17.222 **	10.050 **
26	1.449	1	2.623	1.449	3.181	1	6.366	3.184	6.033	1	12.157	6.125
27	2.383	1	4.730	2.383	1.680	1	4.397	2.717	7.269	1	14.696	7.427
28	4.585 *	3	6.231 *	3.222 *	2.977	1	5.293	2.977	4.234	1	10.276	6.042
29	1.130	1	2.666	1.536	2.433	1	4.658	2.433	8.340 *	1	15.088	8.340
31	2.173	1	3.749	2.173	2.346	1	4.535	2.346	6.296	1	12.245	6.296
34	2.215	1	3.594	2.215	1.217	1	2.797	1.580	15.754 **	3	18.357 **	9.503 **
35	1.961	1	3.327	1.961	3.088	1	5.463	3.088	16.602 **	3	17.403 **	9.511 **
36	1.065	1	3.132	2.067	2.214	1	5.164	2.950	5.896	1	10.773	5.896
37	9.083 ***	3	19.524 ***	11.519 ***	7.347 **	2	12.190 ***	7.052 ***	12.375 *	2	17.015 **	8.803 *
38	4.011 ***	1	6.247 *	4.011 *	7.414 *	3	10.233 **	5.838 **	14.898 *	3	19.153 **	9.608 **
39	4.365 *	3	5.945 *	3.650 *	2.282	1	4.766	2.484	16.371 **	3	16.117 *	8.455 *
41	2.341	1	3.785	2.341	2.206	1	4.201	2.206	4.664	1	9.096	4.664
42	4.299 *	2	5.084	2.866	3.442	1	6.810	3.442	7.124	1	14.536	7.412
43	2.602 *	1	4.265	2.602	2.752	1	5.097	2.752	14.640 *	3	13.073	7.414
44	1.835	1	3.950	2.115	3.360	1	6.316	3.360	5.676	1	10.886	5.676
45	7.456 ***	3	13.353 ***	7.629 ***	4.614 **	1	8.540 **	4.614 *	15.858 **	3	19.071 **	9.860 **
47	1.919	1	3.451	1.919	3.446	1	6.587	3.446	12.333 *	2	15.251	8.002
49	4.170 *	2	4.881	2.780	7.891 **	2	7.400	5.075 **	5.199	1	11.988	6.789
50	1.393	1	3.065	1.673	1.979	1	3.471	1.979	5.565	1	9.318	5.565
51	4.291 *	3	8.375 ***	4.528 ***	3.585	1	6.405	3.585	14.797 *	3	16.606 *	8.934 *
52	4.029 *	2	5.407	2.721	2.880	1	4.914	2.880	4.745	1	9.164	4.745
54	1.104	1	2.266	1.162	2.229	1	4.309	2.229	10.921 ***	1	17.687 **	10.921 **
55	4.272 ***	1	6.144 *	4.272 ***	2.292	1	4.572	2.292	6.347	1	12.036	6.347
56	2.697 *	1	4.215	2.697	3.020	1	5.221	3.020	6.056	1	11.483	6.056
57	3.318 **	1	5.247	3.318 *	3.225	1	6.436	3.225	14.731 *	3	17.243 **	8.697 *
59	1.767	1	3.512	1.767	2.355	1	4.484	2.355	5.677	1	10.426	5.677
60	2.783 *	1	4.967	2.783	3.218	1	5.851	3.218	5.657	1	11.341	5.684
61	1.273	1	3.174	1.901	9.614 ***	2	14.363 ***	7.640 ***	13.876 **	2	18.091 **	9.003 *
62	4.848 **	3	8.900 ***	5.205 ***	3.664	1	7.306	3.664	5.620	1	11.739	6.119
63	1.630	1	3.086	1.630	2.988	1	5.811	2.988	6.232	1	11.507	6.232
64	4.702 **	3	5.030	3.042	2.131	1	5.645	3.515	4.289	1	9.740	5.451
65	4.651 *	3	5.629 *	2.977	2.150	1	5.753	3.602	9.284 **	1	15.931 *	9.284 **
66	1.298	1	2.976	1.678	4.410 *	1	7.833 *	4.410 *	6.299	1	11.717	6.299
67	1.141	1	2.479	1.338	2.423	1	5.148	2.726	5.498	1	12.046	6.547
68	3.304 **	1	5.298	3.304 *	2.625	1	5.705	3.080	5.107	1	11.471	6.364
69	1.826	1	3.635	1.826	2.144	1	4.282	2.144	9.673 **	1	16.608 *	9.673 **
70	0.770	1	1.722	0.952	1.408	1	4.471	3.063	6.592	1	13.079	6.592
72	1.900	1	3.681	1.900	2.454	1	4.800	2.454	14.638 *	3	15.482 *	8.150
73	2.185	1	4.150	2.185	8.408 **	3	7.002	4.032	17.771 **	3	18.258 **	9.055 *
74	1.457	1	3.650	2.193	2.509	1	4.529	2.509	7.833	1	14.257	7.833
75	4.124 *	3	5.242	2.725	1.967	1	4.344	2.378	6.340	1	14.164	7.824

This table reports the results of the $SupQ^{m}$ test for the known number of structural changes and SQ and WQ test that allow an unknown number of regimes. For the $SupQ^{m}$ test, we allow 1 to 3 regime changes under the alternative hypothesis. The trimming proportion is set to 0.2.

Table 6. Summary

comp	GH (1996 a,b)		Johansen et al., (2000)		Qu (2007)		coint	breaks
	strong	weak	no breaks	breaks	strong	weak		
1	Y	Y	N	Y	N	Y	**Y**	**Y**
2	N	Y	N	N	N	Y	**N**	**N**
3	Y	Y	N	Y	N	Y	**Y**	**Y**
4	Y	Y	N	Y	N	N	**Y**	**Y**
5	Y	Y	N	Y	N	Y	**Y**	**Y**
8	N	Y	N	Y	N	Y	**Y**	**Y**
9	N	N	N	N	Y	Y	**Y**	**Y**
10	Y	Y	Y	N	Y	Y	**Y**	**Y**
11	Y	Y	N	Y	Y	Y	**Y**	**Y**
12	Y	Y	Y	N	Y	Y	**Y**	**Y**
14	Y	Y	Y	N	Y	Y	**Y**	**Y**
15	Y	Y	Y	N	N	Y	**Y**	**Y**
16	Y	Y	N	Y	N	Y	**Y**	**Y**
17	Y	Y	Y	N	N	Y	**Y**	**Y**
18	Y	Y	N	N	Y	Y	**Y**	**Y**
19	Y	Y	Y	N	N	Y	**Y**	**Y**
20	Y	Y	N	N	Y	Y	**Y**	**Y**
21	N	N	Y	N	N	N	**Y**	**N**
22	Y	Y	N	Y	Y	Y	**Y**	**Y**
23	Y	Y	N	Y	N	Y	**Y**	**Y**
24	N	N	Y	N	Y	Y	**Y**	**Y**
25	Y	Y	N	Y	Y	Y	**Y**	**Y**
26	Y	Y	N	Y	N	N	**Y**	**Y**
27	Y	Y	N	N	N	N	**Y**	**Y**
28	N	Y	N	N	Y	Y	**Y**	**Y**
29	N	Y	N	Y	N	Y	**Y**	**Y**
31	Y	Y	N	Y	N	N	**Y**	**Y**
34	N	Y	N	Y	Y	Y	**Y**	**Y**
35	Y	Y	Y	N	Y	Y	**Y**	**Y**
36	N	N	N	N	N	N	**N**	**N**
37	N	Y	Y	N	Y	Y	**Y**	**Y**
38	Y	Y	Y	N	Y	Y	**Y**	**Y**
39	N	Y	N	Y	Y	Y	**Y**	**Y**
41	Y	Y	N	N	N	N	**Y**	**N**
42	N	Y	N	N	N	Y	**N**	**N**
43	Y	Y	Y	N	N	Y	**Y**	**N**
44	Y	Y	N	Y	N	N	**Y**	**Y**
45	Y	Y	Y	N	Y	Y	**Y**	**Y**
47	N	N	Y	N	N	Y	**Y**	**N**
49	Y	Y	N	Y	N	Y	**Y**	**Y**
50	N	N	N	N	N	N	**N**	**N**
51	Y	Y	N	Y	Y	Y	**Y**	**Y**
52	N	N	N	N	N	Y	**N**	**N**
54	Y	Y	N	Y	Y	Y	**Y**	**Y**
55	Y	Y	N	Y	Y	Y	**Y**	**Y**
56	Y	Y	N	Y	N	Y	**Y**	**Y**
57	Y	Y	N	Y	Y	Y	**Y**	**Y**
59	N	Y	Y	N	N	N	**Y**	**N**
60	Y	Y	Y	N	N	Y	**Y**	**Y**
61	N	Y	N	N	Y	Y	**Y**	**Y**
62	Y	Y	Y	N	Y	Y	**Y**	**Y**
63	N	N	N	Y	N	N	**Y**	**Y**
64	Y	Y	N	Y	N	Y	**Y**	**Y**
65	Y	Y	N	Y	Y	Y	**Y**	**Y**
66	Y	Y	Y	N	Y	Y	**Y**	**Y**
67	N	Y	Y	N	N	N	**Y**	**N**
68	Y	Y	N	Y	N	Y	**Y**	**Y**
69	N	Y	Y	N	Y	Y	**Y**	**Y**
70	N	Y	N	Y	N	N	**Y**	**Y**
72	N	N	N	N	N	Y	**N**	**N**
73	N	Y	N	N	Y	Y	**Y**	**Y**
74	N	N	N	N	N	N	**N**	**N**
75	Y	Y	N	Y	N	Y	**Y**	**Y**

Table 7. Capital structure arbitrage strategies

Trading strategy	Sample	N	N1	N2	N3	HPR
Panel A: CSA_{pe}	**no coint.**	68.41%	14.04%	1.83%	31.32%	1.58%
	coint.	51.68%	18.23%	1.59%	22.27%	2.32%
	no breaks	43.78%	21.06%	1.36%	20.47%	2.84%
	one break	57.32%	16.68%	1.71%	23.25%	2.04%
Panel B: CSA_{ce}	**coint.**	23.47%	41.32%	1.12%	16.91%	3.02%
	no breaks	17.13%	47.70%	0.76%	14.67%	2.85%
	one break	27.99%	38.53%	1.28%	17.89%	3.10%

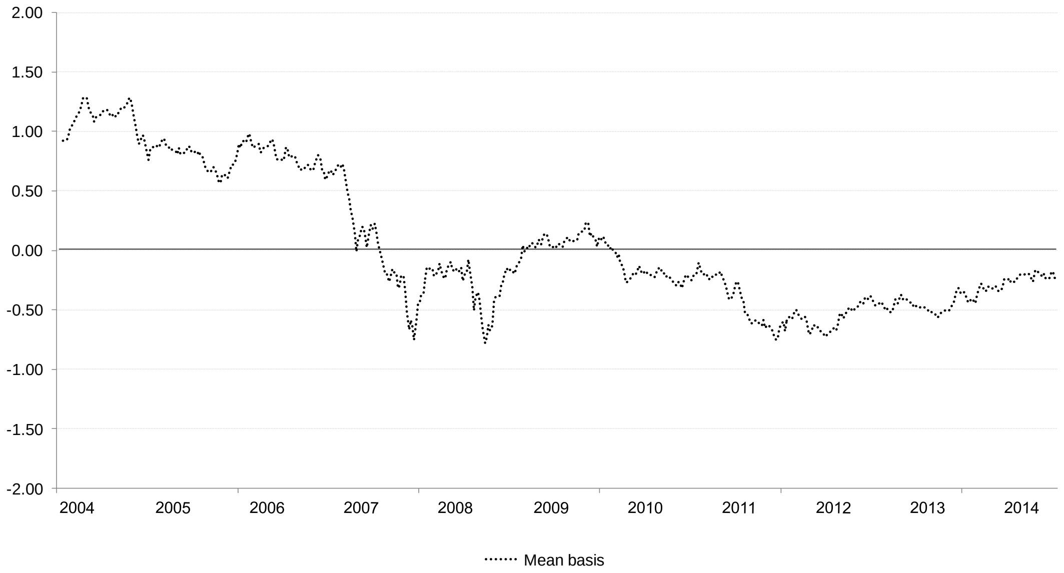
This table reports summary statistics for capital structure arbitrage strategies. N is the fraction of the total number of trades entered into over the total number of available observations. N_1 is the fraction of trades ending in convergence. N_2 is the fraction of trades with drawdown exceeding 20%. N_3 is the number of trades with negative holding period returns. HPR is the mean holding period return.

Table 8. Summary statistics of monthly excess returns

Trading strategy	Sample	Mean	*t-stat*	SD	Min	Max	Skew	Kurtosis	Sharpe ratio
Panel A: CSA_{pe}	**no coint.**	0.15%	1.54	1.15%	-6.75%	5.71%	-1.04	16.83	0.46
	coint.	0.26%	2.25 **	1.31%	-4.68%	6.66%	0.35	9.51	0.68
	no breaks	0.29%	2.49 **	1.35%	-6.49%	6.55%	0.26	11.92	0.75
	one break	0.22%	1.73 *	1.46%	-7.27%	6.77%	-0.22	11.62	0.52
Panel B: CSA_{ce}	**coint.**	0.31%	2.98 ***	1.18%	-3.35%	6.47%	1.25	10.26	0.90
	no breaks	0.26%	2.50 **	1.21%	-3.42%	7.55%	1.49	13.79	0.75
	one break	0.35%	2.81 ***	1.43%	-3.74%	8.48%	1.34	11.06	0.85

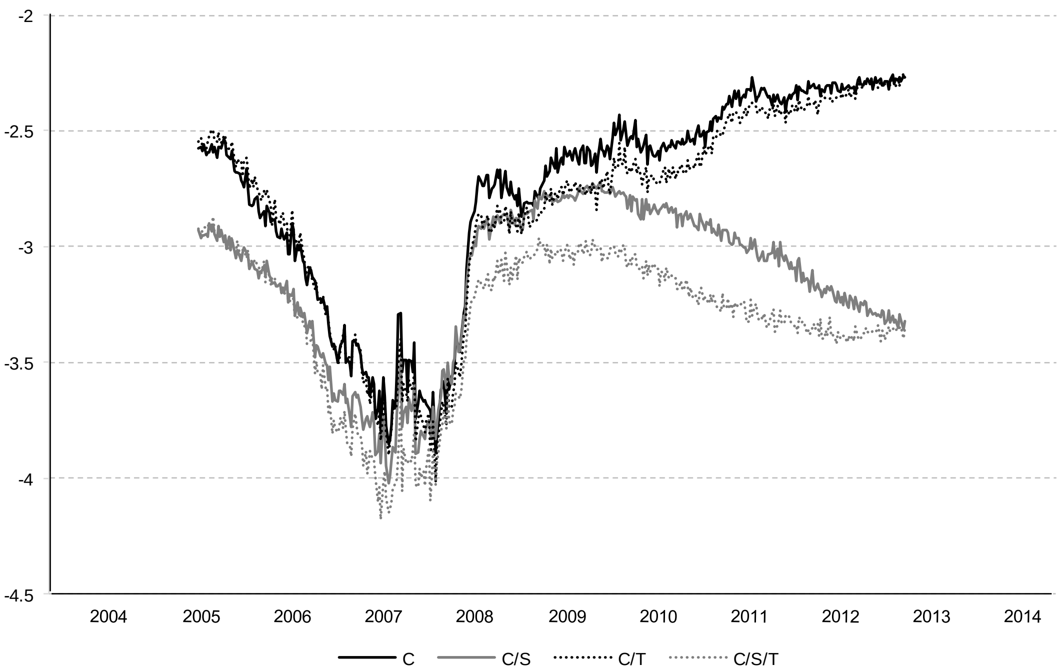
This table reports summary statistics of the monthly index excess returns for sub-samples of companies with cointegrated (no breaks and one break) and non-cointegrated CDS-ICS pairs.

Figure 1. Time development of the mean basis



This figure depicts the time development at a weekly frequency of the mean basis calculated as the cross-sectional mean of the log differences between ICS and CDS spreads.

Figure 2. $ADF(\tau)$ statistics



This figure shows the cross-sectional mean of the $ADF(\tau)$ statistics for models C, C/T, C/S and C/S/T, defined in Equations (5.1)-(5.4). The $ADF(\tau)$ statistics are computed sequentially for each possible break point τ. The trimming parameter is set to 15%.

Appendix A

List of companies

No.	Company	Mean CDS	Mean ICS	No.	Company	Mean CDS	Mean ICS
1	Accor SA	104.16	103.81	39	Lafarge SA	198.97	217.50
2	Airbus Group NV	83.65	80.28	40	Linde AG	50.23	21.23
3	Akzo Nobel NV	66.87	65.04	41	Lufthansa AG	133.51	131.75
4	Anglo American PLC	123.67	122.78	42	LVMH SE	56.02	44.68
5	BAE Systems PLC	81.90	67.56	43	Marks & Spencer PLC	142.82	147.78
6	BAT PLC	55.65	26.80	44	Metro AG	110.99	113.74
7	Bayer AG	51.09	25.95	45	Michelin SCA	107.62	105.77
8	BMW AG	77.56	76.54	46	National Grid PLC	64.53	53.93
9	BP PLC	55.02	61.88	47	Orange SA	70.62	59.95
10	BT Group PLC	84.74	76.97	48	Pearson PLC	57.44	43.66
11	Carrefour SA	72.57	75.90	49	Peugeot SA	250.92	280.45
12	Casino Guichard SA	117.20	109.02	50	Portugal Telecom SGPS SA	230.80	176.87
13	Compass Group PLC	53.73	41.17	51	Renault SA	185.98	194.74
14	Continental AG	244.51	272.20	52	Repsol SA	138.40	146.06
15	Daimler AG	96.51	100.33	53	Rolls-Royce Holdings PLC	62.19	36.34
16	Danone SA	48.64	37.41	54	RWE AG	57.06	51.97
17	Deutsche Telekom AG	70.68	69.41	55	Sainsbury PLC	107.22	100.16
18	Diageo PLC	50.80	36.55	56	Saint Gobain SA	111.89	114.29
19	E.ON SE	56.09	48.83	57	Siemens AG	52.23	50.83
20	Electrolux AB	70.25	69.08	58	Sodexo SA	57.46	37.89
21	EnBW AG	54.19	49.79	59	STMicroelectronics NV	75.34	75.44
22	Endesa SA	93.19	89.36	60	Stora Enso OYJ	232.35	250.74
23	Enel SPA	128.27	142.88	61	Technip	82.54	66.98
24	Energias de Portugal SA	189.26	202.45	62	Telecom Italia SPA	190.17	196.08
25	Finmeccanica SPA	172.17	195.07	63	Telefonica SA	128.11	130.25
26	Fortum OYJ	50.94	42.15	64	Tesco PLC	63.90	55.97
27	GKN PLC	170.10	179.14	65	Total SA	39.76	41.86
28	Hellenic Telecom SA	386.26	539.68	66	Unilever NV	31.31	27.19
29	Henkel & Co KGaA AG	47.33	33.14	67	United Utilities Group PLC	71.67	58.46
30	Holcim Ltd	136.26	140.80	68	UPM Kymmene OYJ	208.72	220.53
31	Iberdrola SA	109.69	89.59	69	Valeo SA	151.16	156.08
32	Imperial Tobacco Group PLC	98.17	58.32	70	Veolia Environnement SA	88.98	84.63
33	Investor AB	66.22	52.81	71	Vodafone Group PLC	66.00	64.07
34	Kering SA	138.05	146.41	72	Volkswagen AG	87.61	45.69
35	Kingfisher PLC	119.73	130.04	73	Volvo AB	128.57	130.62
36	Koninklijke KPN NV	84.37	73.95	74	Wolters Kluwer NV	62.56	57.38
37	Koninklijke Philips NV	58.50	57.23	75	WPP PLC	101.10	101.96
38	Ladbrokes PLC	222.27	223.65				

Appendix B

We compare the explanatory power of ICS for different choices of equity volatility: historical volatility (for estimation horizons of 22, 63, 126, 250 and 1000 days) and constant volatility. Following the current literature, we run firm-specific time-series regressions on a weekly basis, in which changes in CDS spreads are regressed on contemporaneous and one-lag changes in ICS and one-lag changes in CDS spreads:

$$\Delta CDS_{i,t} = \alpha_i + \sum_{k=0}^{1} \beta_{i,t-k} \Delta ICS_{i,t-k} + \gamma_{i,t-1} \Delta CDS_{i,t-1} + e_{i,t} \qquad \text{B.1}$$

Panel A of Table B.1 reports the summary results of the firm-specific regressions and the correlation between changes in CDS spreads and changes in ICS. The mean explanatory power and mean correlation are highest when the volatility parameter is set to a constant. In addition, we corroborate results reported in previous studies that have found that the performance of ICS estimates is worse for volatility measures over short time horizons. These results also hold on the "market" level. Panel B of Table B.1 reports the results from regressing changes in the cross-sectional mean of CDS spreads (CDS_m) on changes in the cross-sectional mean of ICS (ICS_m).

Table B.1. Time-series regressions

Variable	Coefficient	Historical Volatility					constant
		22 days	63 days	126 days	252 days	1,000 days	
Panel A							
constant	α_i	0.06	0.06	0.07	0.10	0.16	0.11
		(0.14)	*(0.16)*	*(0.18)*	*(0.28)*	*(0.50)*	*(0.30)*
$\Delta ICS_{i,t-k,k=0,1}$	$\Sigma\beta_{i,t-k}$	0.02	0.10 **	0.19 ***	0.26 ***	0.50 ***	0.64 ***
		(0.86)	*(2.18)*	*(2.86)*	*(2.63)*	*(3.46)*	*(4.02)*
$\Delta CDS_{i,t-1}$	$\gamma_{i,t-1}$	0.23 ***	0.20 ***	0.20 ***	0.23 ***	0.25 ***	0.26 ***
		(3.18)	*(2.71)*	*(2.93)*	*(3.34)*	*(3.51)*	*(3.57)*
Adj R^2		0.09	0.13	0.15	0.16	0.20	0.21
corr(ΔCDS,ΔICS)		0.10	0.25	0.27	0.27	0.32	0.34
Panel B							
constant	α_m	0.07	0.07	0.09	0.15	0.32	0.11
		(0.20)	*(0.22)*	*(0.31)*	*(0.52)*	*(1.23)*	*(0.48)*
$\Delta ICS_{m,t-k,k=0,1}$	$\Sigma\beta_{m,t-k}$	0.01	0.17 ***	0.32 ***	0.42 ***	1.00 ***	1.25 ***
		(0.32)	*(5.02)*	*(6.82)*	*(4.49)*	*(9.21)*	*(9.60)*
$\Delta CDS_{m,t-1}$	$\gamma_{m,t-1}$	0.21 ***	0.10 **	0.13 **	0.25 ***	0.30 ***	0.32 ***
		(2.82)	*(2.14)*	*(2.57)*	*(4.41)*	*(4.18)*	*(3.52)*
Adj R^2		0.05	0.20	0.25	0.29	0.45	0.49
corr(ΔCDS,ΔICS)		0.09	0.42	0.49	0.49	0.63	0.65

Panel A reports the average coefficients and *t*-statistics (in parentheses) from 75 firm-specific time-series regressions. Panel B reports the coefficients and *t*-statistics (in parentheses) from the time-series regression of changes in the cross-sectional mean of CDS spreads (CDS_m) on changes in the cross-sectional mean of ICS (ICS_m). Standard errors are calculated as Newey–West HAC Standard Errors. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.