Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS

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ABSTRACT

This paper explores the dynamic relationship between stock market implied credit spreads, CDS spreads, and bond spreads. A general VECM representation is proposed for changes in the three credit spread measures which accounts for zero, one, or two independent cointegration equations, depending on the evidence provided by any particular company. Empirical analysis on price discovery, based on a proprietary sample of North American and European firms, and tailored to the specific VECM at hand, indicates that stocks lead CDS and bonds more frequently than the other way round. It likewise confirms the leading role of CDS with respect to bonds.

1. Introduction

Many agents in the economy devote time and effort to the estimation of credit risk in companies, including corporate bondholders, large investment banks ready to cover the risk that bondholders could experience through the sale of such credit derivatives as credit default swaps (CDS), shareholders worried about the possible financial distress their firm could face if its credit rating deteriorated, as well as financial regulators and supervisors.[1] Because credit risk affects all these assets – bonds, CDS, and shares – information about this risk eventually shows in their prices. However, and due to structural differences between markets (organization, liquidity, participants), this information may be incorporated into the price of some of these assets more quickly than others.[2] In this paper, we consider a sample of North American and European companies in order to investigate which of these assets (markets) leads the credit risk discovery process. The analysis is performed on the basis of the credit spread – a homogeneous measure of credit risk for the three markets. Empirical results indicate that stocks lead CDS and bonds more frequently than the other way round, and confirm the leading role of the CDS market with respect to the bond market.

The relative speed with which different markets incorporate new information about the credit risk of companies has been the focus of recent studies. Blanco et al. (2005), for instance, considered a Vector Error Correction Model (VECM) for explaining changes in bond and CDS spreads. Using a sample of 33 North American and European firms, they concluded that the CDS market leads the bond market. In a similar vein, Zhu (2004, 2006) studied an international sample of 24 issuers. He found that the CDS market and the bond market appear to be equally important in the incorporation of new information about the credit risk of companies when the Granger causality test is implemented. When a VECM is used to examine the price discovery process, results change, supporting the leading role of the CDS market.[3]

The first paper to incorporate the stock market in the analysis was Longstaff et al. (2003), who proposed a Vector Auto-Regressive model (VAR) to investigate the lead-lag relationships between changes in CDS spreads, changes in bond spreads, and stock returns. The credit risk discovery analysis was performed by applying

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[1] Understanding the drivers of credit risk (idiosyncratic firm characteristics and systematic factors) is an important issue for the assessment of financial stability. See Bonfim (2009) for evidence on the relative importance of both factors.

[2] For instance, bond and CDS markets are almost entirely institutional, with hardly any retail presence. The stock market, on the other hand, is usually the most liquid.

[3] Ganger causality test results are only reported in Zhu (2004).

the Wald Test over the coefficients of the lagged variables in the VAR model. With a sample of 68 North American companies, they concluded that information flows first into the CDS and the stock markets, and then into the bond market. Norden and Weber (2005) used the same VAR representation to analyze the co-movement of CDS, bond, and stock markets, considering an international sample of 58 companies. For the specific case of CDS and bond markets, they also performed a price discovery analysis using a VECM in line with Blanco et al. (2005) and with Zhu (2004, 2006). Norden and Weber's (2005) results sustain the idea that the stock market leads the CDS and bond markets. Their evidence also supports the leading role of the CDS market with respect to the bond market.

The aim of this paper is to contribute to the literature on market efficiency by analyzing, through a VECM, the relationship between changes in bond spreads (BS), changes in CDS spreads (CDS), and changes in stock market implied credit spreads (ICS). The analysis is based on the same proprietary database on BS, CDS and ICS considered by Forte (2008). More specifically, BS and CDS are related to the ICS generated by a modified version of Leland and Toft's (1996) structural credit risk model, and a novel calibration procedure for the model parameters. Our analysis differs from those of Blanco et al. (2005) and Zhu (2004, 2006), in that we introduce the stock market as a third market into the analysis. It also differs from the analyses of Longstaff et al. (2003) and Norden and Weber (2005), because we deal with credit spreads obtained from the stock market as well as from CDS and bond markets. In this sense it is, as far as we know, the first work in which a *strict price discovery analysis* is performed for the three markets simultaneously.

Using implied credit spreads may prove more appropriate than using stock returns for several reasons. First, from a structural model point of view, credit spreads are a function of many variables; the value of the firm's assets and its volatility, the level of debt and the risk-free rate are but a few examples. If bond spread or CDS spread differentials are related only to stock returns (which could be interpreted as an approximation to variations in the firm asset value), then other relevant variables are being omitted. It would be feasible to follow an approach similar to that of Kwan (1996), correcting the linear model by incorporating changes in the risk-free rate, for instance. However the theory suggests and evidence supports the idea that the relationship between changes in credit spreads on one hand and changes in variables such as the underlying asset value or the risk-free rate on the other is highly non-linear, with this non-linearity better represented by means of a structural model.[4] Stock market implied credit spreads in Forte (2008) account not only for changes in equity prices, but also for changes in risk-free rate, short and long-term liabilities, interest expenses, and cash dividends. Second, in the same way that bond and CDS spreads have been shown to be linearly cointegrated in previous works, we may expect these two series to be linearly cointegrated with implied credit spreads. If this is the case, an additional cointegrating term should be introduced. In other words, the use of stock returns and a VAR representation may suffer from a further problem of omitted variables bias.[5] It is noteworthy that results in Zhu's (2004) paper for CDS and bond markets are largely dependent on the use of a VAR or a VECM representation. Also original to this paper is the consideration of different time periods in addition to different companies: The variables underlying the price discovery process may change not only from company to company for a given period, but also over time within one company.[6]

The remainder of this paper is organized as follows: Section 2 describes the database on stock market implied credit spreads, CDS spreads, and bond spreads. Section 3 discusses the credit risk discovery process in the three markets. Results from other alternative specifications in the credit risk discovery analysis are provided in Section 4. Finally, Section 5 summarizes the main conclusions and proposes future lines of research.

2. Data

Daily data on BS, CDS and ICS correspond to those contained in the final sample of 17 North American and European non-financial firms analyzed by Forte (2008). They span the period 12 September 2001–25 June 2003, with a minimum of 250 observations for all companies. As we intend to investigate the price discovery process considering not only different companies, but also different periods, we divide the sample period into natural half-yearly periods. We therefore have a maximum of four observations for each company, which corresponds to sub-sample periods 1 (year 2001/second half, with observations starting only from 12 September), 2, 3, and 4 (with observations only until 25 June). For all companies we have information for at least 3 consecutive periods, and all periods have at least 50 observations. A detailed description of this sample follows.[7]

2.1. The CDS market

The sample of CDS contains daily data on 5-year premia for 15 European non-financial companies provided by Banco Santander. The data, recorded daily at 17:30 ECT, consist of mid bid-ask spreads for Euro-denominated CDS. The other two companies are highly significant corporations in debt markets: Ford Motor Credit Co. and General Motors Accept. Corp. Data on dollar-denominated CDS (mid bid-ask spreads) for both firms were collected from GFI at the close of the US market (around 17:00 EST).

2.2. The bond market

Times series of 5-year yields in the bond market are estimated in Forte (2008) by searching two bonds satisfying the following criteria:

1. They were designated in local currency.
2. They were without special clauses, such as a buyback clause.

4 Di Cesare and Guazzarotti (2005) show that changes in CDS are better explained by changes in the theoretical credit spreads predicted by Merton's (1974) model than by a linear model that accounts for variations in the underlying variables (leverage, risk-free rate, and volatility).

5 Note also that a cointegration relationship would not need to appear if stock prices were considered instead of ICS. An intuitive example is the case in which both equity capital and debt levels double during a given period. Other things being equal, CDS, BS, and ICS should exhibit a stable pattern (assuming ICS reflect the increased debt level and not merely the higher market capitalization). Stock prices, on the contrary, will show twice their original value.

6 Odders-White and Ready (2006) have documented a negative relationship between credit rating and stock liquidity, for instance, and Longstaff et al. (2005) have obtained a similar result in the case of corporate bonds. Acharya and Johnson's (2007) results indicate on the other hand, that insider trading in credit derivatives generates an information flow from the CDS market to the stock market, but only in days with negative credit news, and for firms that experience or are more likely to experience negative credit events. In a more recent study Dötz (2007) uses the VECM representation to analyze the credit risk price discovery process in CDS and bond markets. His results suggest a slight dominance of the CDS market but also that both markets' contributions may change over time.

7 The number of firms is not particularly high. However, it is in line with other published studies in the field: the number of non-financial companies is 18 in Blanco et al. (2005), 40 in Norden and Weber (2005) and 16 in Zhu (2006). Moreover, Forte (2008) imposes the additional restriction of working with the same (local) currency in the three markets. The selection of natural half-yearly periods may on the other hand appear arbitrary. This however closely corresponds to a homogeneous division of the sample into 4 sub-periods. Such a partition helps in keeping statistical significance, both within each firm-period observation (no less that 50 daily data points, and typically in the order of 120), and among firm-periods observations (60 in the final credit risk discovery analysis).

3. One of the bonds throughout the reference period (the period for which there is information of CDS) has a maturity of less than 5 years but more than 1 year, whereas the other has a maturity of more than 5 years for the entire period.
4. Given these other three characteristics, they are the most recently issued bonds and those that have maturity closer to 5 years.

Carrying out a linear interpolation between the two bonds' yields, estimated series of yields for 5 years were finally derived.

Corporate bond yields satisfying said requirements for the 17 firms were gathered from Datastream. In the case of European companies, these data correspond to mid bid-ask spreads provided to Thomson (Datastream) by the International Capital Market Association (ICMA). ICMA collects closing bid and offer quotes as supplied by members of the Council of Reporting Dealers (CRD), the group that represents the 37 main European market makers. This information is thereafter validated and processed by ICMA, which finally generates an average bid and an average offer. ICMA asserts that data collection occurs daily between 18:00 and 20:45 ECT. The reference timing in Datastream for International Bonds (all in our sample for European companies) is 19:30 ECT. In the case of North American companies, data collected from Datastream correspond to *datatype MP*. Thus, for such companies, bond data are essentially those supplied by local market makers. If available, however, Datastream may complete this information with data from organized exchanges. The reference timing for these bonds, as indicated by Datastream, is 18:00 EST. In this case, as it is for European companies, a certain delay with respect to data availability from the CDS market should be acknowledged. For the estimation of BS, it was finally collected, also from Datastream, 5-year swap rates in both Euros and US dollars.

2.3. The stock market

Stock market ICS are estimated in Forte (2008) using a modified version of Leland and Toft's (1996) structural credit risk model, and a novel calibration procedure for the model parameters.[8] The required inputs are the following:

- D.1. Daily data on stock market capitalization
- D.2. Accounting data referring to:
  - D.2.1. Short-term liabilities
  - D.2.2. Long-term liabilities
  - D.2.3. Interest Expenses
  - D.2.4. Cash Dividends
- D.3. Daily data on swap rates for maturities ranging from 1 to 10 years.

Daily data on market capitalization were obtained from Standard & Poor's.[9] These data are at the close of the local markets: 17:30 ECT in the case of European companies and 16:00 EST for North American companies. Data timing in the stock market therefore match data timing in the CDS market for European firms, but may act in favor of the CDS market in the case of North American companies. As for the bond market, daily data on swap rates were taken from Datastream, with maturities ranging from 1 to 10 years. Finally, accounting data were also collected from Standard & Poor's covering the time interval 31 December 2000–30 June 2003. For some companies, these data were completed using information available from Datastream. Daily values for accounting data items in Forte (2008) were obtained by linearly interpolating those reported at 31 December 2000 and at 30 June 2003.[10]

It is finally worth noting that ICS are estimates, not direct observations, of stock market implied credit spreads. Particularly the assumption of constant bankruptcy costs, firm asset volatility and default point indicator in Forte (2008), and the fact that these unobservable parameters need to be estimated, may lead to measurement errors in ICS series. If these measurement errors have any effect on the credit risk discovery analysis, however, it is to act *against*, but never *in favor*, of the stock market.[11]

Table 1 contains descriptive statistics for the different credit spread series, while Table 2 provides the standard measures of credit spreads differentials: the average basis (*avb*), the percentage average basis (*avb*(%)), the average absolute basis (*avab*), and the percentage average absolute basis (*avab*(%)).[12]

3. Results

If the long run behavior of CDS, BS and ICS, truly reflects the evolution in the 'efficient price of credit risk', then we should expect any pair of these series to be linearly cointegrated. Evidence of a cointegration relationship between CDS and BS has been previously documented by Blanco et al. (2005), Zhu (2004, 2006), and Norden and Weber (2005). We are now in a position to analyze whether or not such a relationship is also present between ICS on one hand, and CDS and BS on the other. Following Forte (2008), however, we find it more appropriate to think of a long run linear relationship between the log of the credit spread series, rather than between the original series themselves. For the rest of the analysis, we therefore consider the log of the ICS series (LICS), the log of the BS series (LBS), and the log of the CDS series (LCDS).

We start by testing the presence of unit roots. Rejection of a unit root at the 95% level of significance is found for Carrefour (LICS), Daimlerchrysler (LCDS), Deutsche Telekom (LBS), KPN (LCDS, LBS), and Siemens (LBS); The presence of a second unit root is always rejected at the 99% level.[13] Johansen Cointegration Trace Test statistics are shown in Table 3. The analysis for any possible pair of non-stationary series (Panel A) and for the most general case that accounts for the three credit spread series simultaneously (Panel B), are included. Note that, in principle, we may expect three possible outcomes from this analysis: The first one should be anticipated whenever the long run behavior of credit spreads in bond, CDS, and stock markets is driven by evolution in the efficient price of credit risk; one cointegration relationship should appear between any pair of series, whereas two independent cointegration relationships should emerge from the joint analysis of the three series. We name this outcome *Model I*. On the contrary, if one of the series is affected either by non-transient factors different from credit risk or

[8] It should be noted that the model is mostly suitable for non-financial firms. For an application of structural models to financial firms see Liao et al. (2009).

[9] In the case of Ford Motor Credit Co. and General Motors Accept. Corp., parent company data were collected.

[10] Although this interpolation is required for ICS to reproduce the long run behavior of the efficient price of credit risk, it could be argued that such a procedure generates a bias in favor of the stock market in the credit risk discovery analysis. This would follow from the fact that ICS incorporate future information on accounting data items. In order to check for this possibility, we repeat the analysis on credit risk discovery by considering alternative ICS series which are estimated by imposing accounting data equal to those reported at close of year 2000. Empirical results (available on request) are not significantly different from those reported in Section 3.

[11] Forte performs two different estimations of the ICS series: one assuming that the default point indicator (the default barrier to total liabilities ratio) is a constant parameter, and the second one allowing this value to change every half-yearly period. In this paper we consider the first set of estimations in order to prevent spurious jumps in the series.

[12] For a detailed description of the estimation of ICS series and of the final sample see Forte (2008).

[13] Rejection of the null hypothesis of non-stationarity is also found for a small subsample of companies in Norden and Weber (2005), Zhu (2006) and Dötz (2007). Unfortunately, results regarding unit root tests in Blanco et al. (2005), with a time span similar to ours, are not provided.

Table 1
Descriptive statistics. This table contains descriptive statistics for the three measures of credit spreads: bond spreads (BS), CDS spreads (CDS), and stock market implied credit spreads (ICS).

	Sector	Obs.	Rating	A: BS				B: CDS				C: ICS			
				Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD
ALCATEL	Equip.	398	Baa1/Baa2/Ba1/B1	130.8	1655.7	567.1	378.9	202.0	1750.0	648.1	418.9	210.9	1632.4	618.1	327.6
BMW	Autos	367	A1	10.7	39.0	24.9	4.9	20.0	52.0	32.6	7.4	7.5	175.8	51.0	39.8
CARREFOUR	Retail	443	A1	15.1	54.2	31.7	9.0	19.0	75.0	34.7	11.6	13.3	122.5	39.3	21.8
DAIMLERCHRYSLER	Autos	444	A3	62.7	185.9	97.5	24.5	87.0	215.0	137.9	23.8	40.7	356.3	156.2	83.9
DEUTSCHE TELEKOM	Telec.	341	A3/Baa1/Baa3	44.1	214.3	150.5	35.2	87.0	405.0	218.8	65.5	97.0	357.3	219.6	60.9
ENDESA	Utilit.	439	Aa3/A2/Baa1	38.3	152.6	69.1	28.5	25.0	205.0	73.1	45.3	19.7	241.7	85.8	59.8
FORD MOTOR CREDIT CO.	Autos	432	A2/A3	100.2	650.0	304.1	131.3	137.0	665.0	317.2	128.2	121.7	673.3	324.2	145.0
FRANCE TELECOM	Telec.	448	A3/Baa1/Baa3	65.6	429.5	172.8	54.5	90.0	660.0	270.9	119.1	77.9	738.9	292.4	162.3
GENERAL MOTORS ACCEP.	Autos	341	A3	88.1	423.8	217.9	81.8	104.5	452.5	242.0	79.4	87.3	413.1	253.9	103.3
KPN	Telec.	452	Baa3/Baa2/Baa1	44.9	826.1	210.6	182.0	60.0	875.0	243.6	187.4	91.8	993.1	243.9	196.7
PHILIPS	Equip.	418	A3/Baa1	43.7	130.1	78.9	21.7	54.0	170.0	101.1	30.2	40.9	268.1	118.3	63.1
PORTUGAL TELECOM	Telec.	311	A3	39.7	172.6	79.5	32.0	38.0	175.0	76.6	31.0	28.0	168.8	77.3	25.1
ROYAL AHOLD	Retail	391	Baa1/Baa3/B1	49.1	1370.5	187.8	262.7	43.0	1750.0	189.1	279.3	35.4	972.2	186.0	213.2
SIEMENS	Equip.	443	Aa3	0.8	54.6	22.0	9.6	31.0	90.0	50.4	13.1	15.2	138.7	61.4	33.2
TELEFONICA	Telec.	366	A2/A3	48.5	203.4	90.6	32.6	38.0	275.0	105.3	56.4	38.9	185.2	98.8	30.9
VEOLIA ENVIRONNEMENT	Utilit.	370	A3/Baa1	54.7	260.0	98.6	27.7	50.0	195.0	100.2	34.5	29.4	362.5	135.7	88.1
VOLKSWAGEN	Autos	346	A1	24.7	63.2	44.1	8.8	25.0	90.0	56.0	16.2	8.3	194.8	81.0	55.5
Mean				50.7	405.0	144.0	78.0	65.3	476.4	170.4	91.0	56.7	470.3	179.0	100.6
SD				32.7	472.4	134.7	104.7	48.7	534.1	152.3	111.4	52.9	410.0	143.4	83.4

by non-transient measurement errors, this series should not be cointegrated with any of the other two series.[14] Moreover, when considering the three simultaneously, one cointegration relationship at most should appear.[15] We name this outcome *Model II*. Finally, if these non-transient features affect more than one of the series, then no cointegration relationship should emerge. We name this outcome *Model III*.

Evidence of Model I is found in Table 3 for Alcatel, BMW, and Ford Motor Credit Co. Model II seems to apply for General Motors Accept. Corp., Portugal Telecom, Telefonica, and Veolia Environnement. In all cases the cointegration relationship appears between LCDS and LBS series. Model III could be appropriate for Carrefour, Daymlerchrysler, Deutsche Telecom, France Telecom, KPN, Siemens, and Volkswagen. For the remaining companies, the evidence is less clear: Endesa shows a cointegration relationship between LCDS and LBS when the pairwise cointegration test is implemented; however, a relationship of this type is not reflected in the simultaneous analysis of the three series.[16] As this last case is the more general representation, we consider Model III appropriate for Endesa. A similar situation is found for Philips: A cointegration relationship appears between LCDS and LBS on one hand and between LICS and LBS on the other. Nevertheless, no relationship emerges when the complete system is analyzed. We again find it more appropriate to look at the general representation and include this company in Model III. The last firm to be classified is Royal Ahold. Whereas clear evidence of one cointegration relationship seems to follow from Panel B, results in Panel A indicate that this could apply either to LCDS–LBS or to LICS–LCDS. In order to verify whether news about accounting irregularities in its American subsidiary, Foodservice, which took place at the end of the sample period were affecting the results, we repeated the analysis considering only the period 2001–2002.[17] As reflected in Table 3, the evidence supports the inclusion of Royal Ahold in Model I, but only for the restricted time interval. Table 4 summarizes the final sample classification into Models I, II, and III.

In spite of the heterogeneity we face in our sample in terms of cointegration relationships, it is possible to define the following general VECM representation for credit spread changes in the three markets:

$$\Delta \mathrm{LCDS}_t = a_1 + \lambda_{11} CE_1 + \lambda_{12} CE_2 + \sum_{z=1}^{Z} b_{1z} \Delta \mathrm{LCDS}_{t-z} + \sum_{z=1}^{Z} c_{1z} \Delta \mathrm{LBS}_{t-z} + \sum_{z=1}^{Z} d_{1z} \Delta \mathrm{LICS}_{t-z} + \varepsilon_{1t}, \quad (1)$$

$$\Delta \mathrm{LBS}_t = a_2 + \lambda_{21} CE_1 + \lambda_{22} CE_2 + \sum_{z=1}^{Z} b_{2z} \Delta \mathrm{LCDS}_{t-z} + \sum_{z=1}^{Z} c_{2z} \Delta \mathrm{LBS}_{t-z} + \sum_{z=1}^{Z} d_{2z} \Delta \mathrm{LICS}_{t-z} + \varepsilon_{2t}, \quad (2)$$

$$\Delta \mathrm{LICS}_t = a_3 + \lambda_{31} CE_1 + \lambda_{32} CE_2 + \sum_{z=1}^{Z} b_{3z} \Delta \mathrm{LCDS}_{t-z} + \sum_{z=1}^{Z} c_{3z} \Delta \mathrm{LBS}_{t-z} + \sum_{z=1}^{Z} d_{3z} \Delta \mathrm{LICS}_{t-z} + \varepsilon_{3t}, \quad (3)$$

14 See Blanco et al. (2005). An alternative explanation for the lack of cointegration between any pair of series is that the corresponding markets systematically assign different credit spreads to the same company. This would imply the existence of arbitrage opportunities, however.

15 Of course, the absence of cointegration relationships also follows from the stationarity in the log of credit spread series.

16 Our general criterion is to consider the 95% level as the standard rejection level. However, the omission of a significant error correction term may prove more harmful than the inclusion of a non-significant term. For this reason, we proceed by adopting the 90% level in this case.

17 ADF Tests are performed for this restricted time interval. Results confirm the presence of a unit root in all credit spread series for Royal Ahold.

Table 2
Basis. Standard measures of credit spreads differentials are provided in this table: the average basis (*avb*), the percentage average basis (*avb* (%)), the average absolute basis (*avab*) and the percentage average absolute basis (*avab* (%)).

	A: CDS vs BS				B: ICS vs CDS				C: ICS vs BS			
	avb	*avab* (%)	*avab*	*avab* (%)	*avb*	*avab* (%)	*avab*	*avab* (%)	*avb*	*avab* (%)	*avab*	*avab* (%)
ALCATEL	81.02	22.02	119.33	26.98	−30.03	3.57	136.15	19.99	50.99	22.11	102.60	26.93
BMW	7.78	32.24	8.03	33.08	18.33	44.01	29.46	84.86	26.12	91.42	31.80	118.35
CARREFOUR	3.01	15.73	10.69	37.51	4.64	10.48	12.19	33.32	7.65	40.77	20.16	75.41
DAIMLERCHRYSLER	40.38	44.32	40.41	44.34	18.30	17.38	77.40	60.10	58.68	66.08	72.13	80.95
DEUTSCHE TELEKOM	68.35	46.71	68.55	46.88	0.77	4.66	39.70	21.05	69.12	48.70	69.92	49.33
ENDESA	4.07	1.62	16.65	24.61	12.62	10.99	24.05	32.72	16.69	12.71	34.45	49.95
FORD MOTOR CREDIT CO.	13.11	6.00	22.00	8.50	7.01	1.11	39.52	11.65	20.12	6.82	40.84	13.18
FRANCE TELECOM	98.04	52.37	98.12	52.44	21.54	8.54	80.02	33.42	119.58	63.85	130.01	71.14
GENERAL MOTORS ACCEP.	24.12	13.38	26.74	14.15	11.88	3.16	48.28	19.94	36.00	16.08	52.02	23.09
KPN	33.01	21.14	37.77	22.15	0.29	3.24	44.22	19.81	33.30	23.12	43.46	26.49
PHILIPS	22.16	30.57	23.15	31.82	17.19	17.50	48.24	48.43	39.36	46.38	49.22	57.97
PORTUGAL TELECOM	−2.94	−2.91	7.25	9.59	0.69	10.83	24.01	35.25	−2.25	8.33	27.31	38.96
ROYAL AHOLD	1.36	−2.86	21.06	12.32	−3.15	5.16	41.80	19.48	−1.79	2.82	45.10	25.91
SIEMENS	28.40	193.08	28.42	193.13	11.09	22.74	26.12	55.44	39.49	207.61	40.06	209.52
TELEFONICA	19.15	18.07	19.57	18.77	−6.44	8.35	32.63	33.95	8.24	17.61	27.99	36.37
VEOLIA ENVIRONNEMENT	1.57	0.23	10.65	10.85	35.80	42.86	71.04	78.61	37.36	44.32	72.85	81.83
VOLKSWAGEN	11.86	25.76	13.69	30.53	24.95	30.57	39.41	66.73	36.81	75.16	49.89	109.44
Mean	26.73	30.44	33.65	36.33	8.56	14.42	47.90	39.69	35.03	46.70	53.52	64.40
SD	29.66	45.27	32.16	42.59	14.87	13.40	29.53	22.25	29.61	49.06	28.60	48.29

Table 3
Johansen Cointegration Tests. This table contains Johansen Cointegration Trace Test statistics. The analysis is performed for any possible pair of non-stationary series (Panel A), and for the most general case that accounts the three series simultaneously (Panel B). A constant is allowed both in the cointegration equation and in the VAR component of the VECM. The number of lags is selected according to the Schwarz criterion.

	A						B		
	LCDS-LBS		LICS-LCDS		LICS-LBS		LCDS-LBS-LICS		
	None	At most 1	None	At most 1	None	At most 1	None	At most 1	At most 2
ALCATEL	48.3531***	2.3005	20.5201***	1.4510	20.0747***	0.9212	74.1206***	14.8202*	2.0712
BMW	20.6369***	2.6840	16.2416**	0.8949	21.3397***	1.1774	50.3779***	16.7656**	1.0343
CARREFOUR	6.0088	1.5501	–	–	–	–	–	–	–
DAIMLERCHRYSLER	–	–	–	–	11.6238	2.0758	–	–	–
DEUTSCHE TELEKOM	–	–	8.4744	1.3446	–	–	–	–	–
ENDESA	13.7779*	1.4686	11.1589	1.4630	7.3888	1.3610	24.1781	7.4416	1.5407
FORD MOTOR CREDIT CO.	68.4858***	3.5949*	16.5084**	2.6484	31.9555***	2.5447	84.8722***	17.7416**	2.7677*
FRANCE TELECOM	10.0350	0.1301	4.4189	0.3080	1.8503	0.2568	19.2745	2.9314	0.0158
GENERAL MOTORS ACCEP.	44.2526***	1.5426	5.8996	0.5168	7.7819	0.4659	49.9422***	6.3412	0.4951
KPN	–	–	–	–	–	–	–	–	–
PHILIPS	16.2705**	2.7091*	7.4792	0.5734	14.5630*	2.2564	26.7325	9.1277	1.6782
PORTUGAL TELECOM	15.3214*	0.2162	7.5198	0.8405	8.3136	0.0113	28.1071*	9.0801	0.0048
ROYAL AHOLD	16.0149**	0.1733	19.7217**	0.0026	9.2045	0.0595	42.6541***	8.5562	0.0424
ROYAL AHOLD (2001–2002)	14.7836*	0.0536	27.1120***	0.0233	15.0986*	0.2315	42.2477***	13.6914*	0.2348
SIEMENS	–	–	8.6812	1.6302	–	–	–	–	–
TELEFONICA	16.9444**	1.9819	10.5513	0.4783	12.1527	0.5065	27.9742*	11.4768	1.9730
VEOLIA ENVIRONNEMENT	49.8649***	2.3103	6.2688	1.5950	5.2480	0.6856	61.0846***	5.7651	1.0132
VOLKSWAGEN	13.2769	2.8152*	12.4279	0.9376	8.2559	1.0667	26.6482	8.2990	1.1335

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

Table 4
Firm classification. Firms are classified either in Model I (two independent cointegration equations), Model II (one cointegration equation) or Model III (zero cointegration equations). The cointegration equation in Model II, is in our sample always between LCDS and LBS.

Model I	Model II	Model III
ALCATEL	GENERAL MOTORS ACCEP.	CARREFOUR
BMW	PORTUGAL TELECOM	DAIMLERCHRYSLER
FORD MOTOR CREDIT CO.	TELEFONICA	DEUTSCHE TELEKOM
ROYAL AHOLD (2001–2002)	VEOLIA ENVIRONNEMENT	ENDESA
		FRANCE TELECOM
		KPN
		PHILIPS
		SIEMENS
		VOLKSWAGEN

where ε_{1t}, ε_{2t} and ε_{3t} are *i.i.d* error terms. Depending on whether we are concerned with Model I, II, or III, some restrictions will apply to this general representation:

Model I: Two independent cointegration equations:

$$CE_1 = \text{LCDS}_{t-1} - \phi_{11} - \phi_{21}\text{LICS}_{t-1}, \tag{4}$$

$$CE_2 = \text{LBS}_{t-1} - \phi_{12} - \phi_{22}\text{LICS}_{t-1}. \tag{5}$$

Model II: One cointegration equation relating LCDS and LBS:[18]

$$CE_1 \equiv CE = \text{LCDS}_{t-1} - \phi_1 - \phi_2\text{LBS}_{t-1}, \tag{6}$$

$$CE_2 = 0; \quad \lambda_{11} \equiv \lambda_1; \quad \lambda_{21} \equiv \lambda_2; \quad \lambda_{31} = 0. \tag{7}$$

Model III: Zero cointegration equations:

$$CE_1 = CE_2 = 0. \tag{8}$$

A strict price discovery analysis for the three markets can be performed only for companies included in Model I. The fact that LICS do not appear linearly cointegrated with LCDS and LBS in Model II suggests that non-transient factors permanently divert ICS series from the efficient price of credit risk. Nonetheless, price discovery analysis is still feasible for LCDS and LBS series. As a matter of fact, we may see Blanco et al. (2005), Zhu (2004, 2006) and Norden and Weber (2005) models for CDS and bond spread changes as a particular case of Model II in which changes in stock market implied credit spreads are not accounted for.[19] At the same time, analysis of the coefficients of the VAR component in the VECM, still allows us to derive conclusions about the leading role of the stock market with respect to CDS and bond markets. In this sense, Longstaff et al. (2003) and Norden and Weber (2005) models for changes in CDS premia, changes in bond spreads, and stock returns, could also be seen as a particular case of Model II, where, in addition to using stock returns instead of changes in implied credit spreads, the error correction term between CDS and bond market spreads is omitted. Finally, for companies included in Model III, the leading role of the different markets can be analyzed by means of a differenced VAR, in a similar vein to that proposed by the latter authors.

Model I: Table 5 shows coefficient estimates for cointegration equations in Model I. Values obtained from the entire sample period are displayed in Panel A. A first exploratory analysis suggests that, for firms included in this model, results are consistent with a leading role of the stock market. To see why this should be the case, note first that if the stock market leads the CDS market, then we should expect λ_{11} to be negative and significant and λ_{31} not to be statistically different from zero. This happens in 3 out of 4 cases. At the same time, if the stock market leads the bond market, then λ_{22} should be significant with a negative sign and λ_{32} should not be statistically different from zero. Considering 5% to be the cutoff level for significance, we conclude that this happens in all cases. For the estimation of cointegration equation coefficients in different sub-periods, we proceed by imposing on the model the cointegration equations derived from the entire sample period analysis. Results, as exhibited in Panel B, are generally consistent with those provided by Panel A. Nonetheless, it seems that considering different time periods generates a more detailed picture of the price discovery process. As an example, although the stock market tends to lead the CDS market in the case of Ford Motor Credit Co. (Panel A), the contrary happened during the second half of 2001 (Panel B).

Cointegration equation coefficients provide valuable information on the price discovery process; however, they do not represent direct estimates of market information shares. Two alternative approaches for estimating these shares in cointegrated systems, such as the one described by Model I, are due to Hasbrouck (1995) and Gonzalo and Granger (1995) (GG). Whereas Hasbrouck (1995) decomposes the implicit efficient price variance and attributes a greater share of the efficient price discovery to the market that contributes most to this price variance, GG decomposes the permanent component itself and, ignoring the correlation between markets, attributes the leading role solely to the market that adjusts least to the price movements in the other markets. Baillie et al. (2002) maintain that both approaches are complementary rather than substitutive, as they supply different views of the price discovery process. Ordering of variables is crucial in Hasbrouck's approach, leading to upper and lower bounds in markets' information shares. As suggested by Baillie et al. (2002), we use the midpoint of these bounds (HM).

GG and Hasbrouck's measures are contained in Table 6, in which results for both the entire sample period analysis (Panel A) and the sub-periods analysis (Panel B) are reported. GG estimates are out of the acceptable range [0, 1] at times, as has been observed in previous studies (Blanco et al. (2005)). Nonetheless, both GG and HM measures provide broadly consistent results.

Information shares in Table 6 confirm the leading role of the stock market for companies included in Model I. If we first focus on the analysis of the entire sample (Panel A), HM (GG) suggests that 61% (70%) of the price discovery occurs in the stock market, 31% (39%) in the CDS market, and 9% (−9%) in the bond market. Looking at different sub-periods (Panel B), HM (GG) allocates 51% (68%) of the price discovery to the stock market, 31% (27%) to the CDS market, and 18% (5%) to the bond market. Results also support the view that contributions to price discovery are time varying. For instance the CDS market's highest contributions more usually took place in sub-period 2 (3 out of 4 companies).[20] On the contrary, the stock market's highest contributions clearly concentrated in sub-period 3 (all cases). Therefore, it appears that considering different time periods provides in fact a more detailed picture of the price discovery process than relying only on the standard cross-sectional analysis.[21]

Model II: Coefficient estimates for the cointegration equation in Model II are displayed in Table 7. Note that a negative and significant value for λ_1 implies that the bond market makes a significant contribution to price discovery. If, on the other hand, λ_2 proves to be significant with a positive sign, then a non-negligible part of this price discovery takes place in the CDS market. Looking at the entire sample period analysis (Panel A), no clear evidence of a leading role for either of these two markets is found; the coefficient λ_1 is significant with the predicted sign in 2 out of 4 cases, whereas λ_2 is significant, also with the predicted sign, for 3 of the companies. Analysis of different sub-periods does not change the conclusions; the bond market contributes in 5 out of 12 possible cases, and the same can be said with respect to the CDS market.

Information share estimates are shown in Table 8. As expected from previous analysis, both CDS and bond markets exhibit significant contributions to price discovery. Notwithstanding, results suggest a higher information share for the CDS market. This general conclusion is equally supported by GG (60% information share for the CDS market vs. 40% for the bond market in light of sub-periods analysis) and HM (56% vs. 44%).

As we previously argued, cointegration test results suggest that for companies in Model II, non-transient components (factors that differ from credit risk or permanent measurement errors) tend to

[18] We assume that changes in LICS are independent of this cointegration equation.

[19] Of course, an additional difference is the use the log of credit spread series in our case.

[20] Interestingly, Alexander and Kaeck (2008) report that CDS are extremely sensitive to stock market volatility during periods of CDS market turbulence, but in ordinary market circumstances CDS spreads are more sensitive to stock returns than they are to stock volatility.

[21] The detailed investigation of factors underlying the price discovery process – as much in the time series as in the cross-section – seems a promising line of research, but beyond the scope of the present study. For a first attempt in this direction in the case of CDS and bond markets see Dötz (2007).

Table 5
Model I: Coefficients. This table shows the coefficients of the cointegration equations in Model I. The number of lags in the VAR component of the VECM is selected according to the Schwarz criterion for the Entire Sample Period case.

	Δ LCDS		Δ BS		Δ LICS	
	λ_{11}	λ_{12}	λ_{21}	λ_{22}	λ_{31}	λ_{32}
A: Entire sample period						
ALCATEL	−0.0034	−0.0291	0.0918***	−0.1507***	0.0558***	−0.0353*
BMW	−0.0742***	0.0224	0.0736*	−0.2302***	0.0335	−0.0494
FORD MOTOR CREDIT CO.	−0.1405***	0.1218***	0.1639***	−0.2131***	−0.0076	0.0622*
ROYAL AHOLD (2001–2002)	−0.1173***	0.0292	0.0175	−0.0641***	0.0232	−0.0283
B: Different sub-periods						
ALCATEL 1	−0.1578**	0.1192	0.1243*	−0.1825***	0.1695**	−0.1430*
ALCATEL 2	−0.0589	0.0690	0.2126***	−0.2908***	0.0972***	−0.0481
ALCATEL 3	−0.0128	−0.0339	0.0464***	−0.0918***	0.0110	−0.0033
ALCATEL 4	−0.0445	0.0883	0.1377***	−0.3172***	−0.0190	0.3172**
BMW 2	−0.0974**	0.0236	−0.0431	−0.3028***	0.1267	0.0075
BMW 3	−0.0910**	0.0367	0.1316**	−0.2614***	0.0599	−0.1182
BMW 4	−0.1015***	−0.0124	−0.0451	−0.1356**	−0.0610	−0.0988
FORD MOTOR CREDIT CO. 1	−0.0766	0.0557	0.5642***	−0.4897***	0.3350**	−0.1117
FORD MOTOR CREDIT CO. 2	−0.1943***	0.1280**	0.2638**	−0.3630***	−0.0810	0.1425*
FORD MOTOR CREDIT CO. 3	−0.4376***	0.3172***	0.0565	−0.1262	−0.1287	0.1103
FORD MOTOR CREDIT CO. 4	−0.2375***	0.1721**	−0.0720	0.0126	−0.0866	0.1446**
ROYAL AHOLD 1	−0.0721	0.0856	0.0418	−0.1286	−0.0201	0.3165***
ROYAL AHOLD 2	−0.1001**	0.0542	0.0920**	−0.2241***	0.0424	0.1257
ROYAL AHOLD 3	−0.1541***	0.0173	0.0022	−0.0680**	0.0078	−0.0372

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

divert ICS from the efficient price of credit risk. This does not mean that credit risk information is not incorporated into ICS, as it is into CDS or BS. However, analysis of the coefficients of the VAR component in the VECM turns out to be the appropriate method for investigating the leading role of different markets in this context. If we reject the null hypothesis that present changes in LCDS (LBS) are independent of past changes in LICS, for example, but cannot reject the inverse hypothesis (we call this an exclusive rejection), then we may conclude that the stock market is incorporating more timely information than is the CDS (bond) market.

Table 8 summarizes results emerging from this analysis. Looking at Panel A, for instance, we find in the case of General Motors Accept. Corp. that the null hypothesis of present changes in LCDS, being independent of past changes in LICS, is rejected (the *F*-statistic for the corresponding Wald Test is 12.57, which is significant at the 1% level). The inverse however is not true and therefore,

Table 6
Model I. Information Shares. Both GG and Hasbrouck's measures of information shares are provided in this table.

	GG			Hasbrouck								
				Lower Bound			Upper Bound			Mid Point		
	LCDS	LBS	LICS	LCDS	LBS	LICS	LCDS	LBS	LICS	LCDS	LBS	LICS
A: Entire sample period												
ALCATEL	0.81***	−0.18	0.38***	0.83	0.00	0.10	0.90	0.02	0.15	0.86	0.01	0.13
BMW	0.25**	−0.13	0.89***	0.02	0.01	0.92	0.07	0.02	0.96	0.05	0.01	0.94
FORD MOTOR CREDIT CO.	0.31***	0.29***	0.39***	0.10	0.08	0.26	0.47	0.46	0.62	0.28	0.27	0.44
ROYAL AHOLD (2001–2002)	0.18	−0.32*	1.14***	0.01	0.04	0.94	0.06	0.06	0.95	0.03	0.05	0.95
Mean	0.39	−0.09	0.70	0.24	0.03	0.56	0.37	0.14	0.67	0.31	0.09	0.61
B: Different sub-periods												
ALCATEL 1	0.54***	−0.15	0.62***	0.35	0.00	0.47	0.53	0.02	0.63	0.44	0.01	0.55
ALCATEL 2	0.77***	0.15*	0.08	0.93	0.03	0.00	0.95	0.06	0.03	0.94	0.05	0.02
ALCATEL 3	0.31***	−0.13	0.82***	0.13	0.01	0.59	0.32	0.12	0.86	0.23	0.06	0.73
ALCATEL 4	0.73***	0.23**	0.04	0.81	0.01	0.00	0.98	0.19	0.05	0.90	0.10	0.02
BMW 2	0.54***	0.05	0.42***	0.17	0.02	0.78	0.18	0.04	0.81	0.17	0.03	0.80
BMW 3	−0.13	−0.86**	1.99***	0.00	0.05	0.91	0.03	0.06	0.93	0.02	0.06	0.92
BMW 4	−0.04	−0.08	1.12***	0.00	0.02	0.59	0.03	0.04	0.83	0.02	0.03	0.71
FORD MOTOR CREDIT CO. 1	0.87***	0.08*	0.05*	0.72	0.02	0.00	0.98	0.05	0.20	0.85	0.03	0.10
FORD MOTOR CREDIT CO. 2	0.12**	0.28***	0.60***	0.01	0.16	0.53	0.15	0.43	0.79	0.08	0.30	0.66
FORD MOTOR CREDIT CO. 3	−0.24	0.27***	0.97***	0.02	0.07	0.77	0.11	0.20	0.92	0.07	0.13	0.84
FORD MOTOR CREDIT CO. 4	−0.47*	0.97***	0.50***	0.08	0.57	0.17	0.08	0.81	0.43	0.08	0.69	0.30
ROYAL AHOLD 1	0.28***	0.57***	0.15**	0.15	0.67	0.05	0.26	0.74	0.11	0.21	0.71	0.08
ROYAL AHOLD 2	0.38***	0.27***	0.34***	0.27	0.15	0.35	0.39	0.33	0.53	0.33	0.24	0.44
ROYAL AHOLD 3	0.07	−0.90**	1.83***	0.000	0.00	0.91	0.01	0.09	0.99	0.01	0.04	0.95
Mean	0.27	0.05	0.68	0.26	0.13	0.44	0.36	0.23	0.58	0.31	0.18	0.51

For GG estimates:
* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

Table 7
Model II: Coefficients. This table shows the coefficients of the cointegration equation in Model II. The number of lags in the VAR component of the VECM is selected according to the Schwarz criterion for the Entire Sample Period case.

	λ_1	λ_2
A: Entire sample period		
GENERAL MOTORS ACCEP.	−0.0010	0.2241**
PORTUGAL TELECOM	−0.1108**	−0.0116
TELEFONICA	0.0033	0.0215**
VEOLIA ENVIRONNEMENT	−0.1601**	0.0721**
B: Different sub-periods		
GENERAL MOTORS ACCEP. 2	−0.0042	0.4266**
GENERAL MOTORS ACCEP. 3	0.0044	0.1711**
GENERAL MOTORS ACCEP. 4	−0.0488	0.1129*
PORTUGAL TELECOM 2	−0.0754	0.0332
PORTUGAL TELECOM 3	−0.2198**	−0.0431
PORTUGAL TELECOM 4	−0.1467**	−0.0155
TELEFONICA 2	−0.0018	0.0080
TELEFONICA 3	0.0041	0.0166*
TELEFONICA 4	−0.0472	0.0121
VEOLIA ENVIRONNEMENT 2	−0.3127**	0.0607
VEOLIA ENVIRONNEMENT 3	−0.0783*	0.2605**
VEOLIA ENVIRONNEMENT 4	−0.1305**	−0.0157

* Indicates significance at the 5% level.
** Indicates significance at the 1% level.

considering the entire sample period, the stock market seemed to lead the CDS market for this specific company. Applying similar arguments to the sub-periods analysis (Panel B), we conclude that in 3 out of 12 cases the stock market led the CDS market, whereas the inverse never happened. Finally, the stock market led the bond market in just one case, and never the other way round.

Model III: Table 9 shows results from the analysis of lead-lag relationships between the three possible pairs of series. Both the entire sample period analysis (Panel A) and the sub-periods analysis (Panel B) indicate a clear pattern of leadership from the CDS market to the bond market. Looking at the detailed level of sub-periods, the CDS market led the bond market in 9 out of 34 cases, whereas the contrary was true in only one case. At the same time, the stock market seemed to lead the CDS market in 9 out of 34 cases as well, against only one case for the opposite. Surprisingly, these results do not translate into a clear evidence of leadership from the stock market to the bond market. As a matter of fact, the bond market seemed to lead the stock market according to the entire sample analysis: 3 cases out of 9 against 1 case for a leading role of the stock market. Results reverse in the sub-periods analysis, however, as numbers change to 2 and 3, respectively. A lack of clear evidence in favor of any of the two markets seems, in any case, not to be due as much to a similar number of leadership relationships as to the small number of relationships *per se*. This is consistent with Blanco et al. (2005) and Norden and Weber (2005), who found the link between CDS and stock markets stronger than the link between bond and stock markets. They both relate this result to the influence of macro factors, different from credit risk, on BS changes.[22] It is worth noting that price discovery analysis in Model I, which is based on the long run equilibrium relationship between credit spread series, provides clear evidence in favor of the stock market.

Heterogeneity of firms and models may limit the ability to derive general conclusions about the leading role of the three markets. One simple way to overcome this problem is to define a dummy variable, $D(A, B)$, when comparing markets A and B for a given firm and time period. This variable takes value 1 whenever any of the following conditions are met, and 0 otherwise:

1. Market A has a higher information share than market B according to GG and HM.
2. Present changes in the log of credit spreads for market A are independent of past changes in the log of credit spreads for market B, but not the opposite.

The first condition applies in Model I and it also applies in Model II when comparing CDS and bond markets. The second condition applies when comparing CDS and stock markets, and also in comparing bond and stock markets, both in Model II. It finally applies to any possible pairwise comparison in Model III. If $D(A, B)$ equals 1, then we may conclude that, independently of whether or not the logs of the credit spread series are cointegrated, market A led market B in the 'credit risk discovery process'.

Table 10 shows the sum of the dummy variables as well as their averages. The table also provides the Z-statistic, testing the null hypothesis of equality of means. Results for both, the entire sample period analysis (Panel A) and the sub-periods analysis (Panel B), are included in the table. According to Panel A, in 10 cases the stock market led the CDS market, while the opposite was true in one case. Also in seven cases the stock market led the bond market, being the contrary true in 3 cases. These positive differences (9 and 4, respectively) suggest the leading role of stocks, which is highly significant for CDS and, to a lesser extent, for bonds. On the other hand, the CDS market led the bond market in eight occasions, being the opposite true in three cases. The positive and significant difference (5) confirms the leading role of the CDS with respect to the bond market reported in previous studies.[23]

In Panel B stocks lead CDS in 20 cases and lead bonds in 13 cases. The opposite is true in 6 cases for bonds and five cases for CDS. As in Panel A, the difference between cases suggests the leading role of stocks. This leading role is highly significant for CDS and, as indicated by the test of equality of means, to a lesser extent for bonds. Also, CDS lead bonds in 23 cases being the opposite true in 10 cases, confirming the previous comment on the role of CDS.

Overall, results are consistent with the view that the stock market leads the CDS and bond markets more often than vice versa, and also confirm the leading role of the CDS market with respect to the bond market.

4. Alternative specifications

4.1. Exogenous default point parameter

In the methodology proposed by Forte (2008) the default barrier is calibrated from CDS data. It could be argued that the presence of a cointegration relationship between LICS series and the other time series (LCDS and LBS) is to some extent a consequence of this calibration procedure. To check for this possibility we repeat the analysis by considering alternative ICS series where the default point parameter, β, is exogenously fixed at 0.73 (Leland (2004)). Table 11 contains cointegration test statistics resulting from this alternative specification.[24] Compared to those reported in Section 2 (Table 3)

[22] See also Collin-Dufresne et al. (2001).

[23] Norden and Wagner (2008) find that CDS spreads are important determinants of bank loan spreads which suggests that the markets for CDS have an important role for banks as well.

[24] ADF Tests produce roughly the same results as those derived from the original time series. The sole exception is KPN; the presence of a unit root is now rejected at the 95% level also in the case of LICS.

Table 8

Model II: Information shares and lead-lag relations. This table shows both GG and Hasbrouck's measures of information shares for CDS and bond markets. It also contains results of lead-lag relations analysis between LICS on one hand, and LCDS and LBS on the other. Specifically, the table provides the *F*-statistics that come out from testing, by means of the Wald Test, the null hypothesis that present changes in one given market are independent of past changes in a different market.

	LCDS vs. LBS								LICS vs. LCDS		LICS vs. LBS	
	GG		Hasbrouck									
			Lower bound		Upper bound		Midpoint		Δ LCDS/ L(Δ LICS)	Δ LICS/ L(Δ LCDS)	Δ LBS/ L(Δ LICS)	Δ LICS/ L(Δ LBS)
	LCDS	LBS	LCDS	LBS	LCDS	LBS	LCDS	LBS				
A: Entire sample period												
GENERAL MOTORS ACCEP.	1.04***	−0.04	0.80	0.00	1.00	0.20	0.90	0.10	12.5751***	0.0001	14.9620***	0.4698
PORTUGAL TELECOM	−0.04	1.04***	0.00	0.88	0.12	1.00	0.06	0.94	3.5005*	0.0000	1.1504	0.8068
TELEFONICA	1.24***	−0.24	0.99	0.02	1.00	0.03	0.99	0.03	14.4198***	1.9720	2.2278	0.0181
VEOLIA ENVIRONNEMENT	0.24***	0.76***	0.08	0.65	0.35	0.92	0.22	0.78	0.6344	1.4379	4.6163**	0.1267
Mean/Ex. rej. at 5% level	0.62	0.38	0.47	0.39	0.62	0.54	0.54	0.46	2	0	2	0
B: Different sub-periods												
GENERAL MOTORS ACCEP. 2	0.99***	0.01	0.92	0.00	1.00	0.08	0.96	0.04	6.1907**	0.1467	6.7961**	0.2118
GENERAL MOTORS ACCEP. 3	1.02***	−0.02	0.66	0.00	1.00	0.34	0.83	0.17	2.4777	0.1793	3.9014*	2.2147
GENERAL MOTORS ACCEP. 4	0.70***	0.30**	0.39	0.07	0.93	0.61	0.66	0.34	2.3095	0.1120	2.4024	0.1753
PORTUGAL TELECOM 2	0.15**	0.85***	0.08	0.65	0.35	0.92	0.22	0.78	0.4625	0.5841	0.2656	0.2036
PORTUGAL TELECOM 3	1.19***	−0.19*	0.73	0.01	0.99	0.27	0.86	0.14	1.6912	0.0205	0.4296	0.6038
PORTUGAL TELECOM 4	−0.11	1.11***	0.01	0.98	0.02	0.99	0.01	0.99	1.4064	0.0271	3.5028*	0.1459
TELEFONICA 2	0.89***	0.11*	0.96	0.01	0.99	0.04	0.98	0.02	7.3887***	0.5247	0.8626	0.3114
TELEFONICA 3	1.33***	−0.33*	0.98	0.00	1.00	0.02	0.99	0.01	2.9540*	0.6414	0.6134	0.9340
TELEFONICA 4	0.20**	0.80***	0.13	0.73	0.27	0.87	0.20	0.80	1.7714	1.9361	0.0780	0.0375
VEOLIA ENVIRONNEMENT 2	0.16**	0.84***	0.06	0.54	0.46	0.94	0.26	0.74	0.0229	0.1524	0.3637	2.4119
VEOLIA ENVIRONNEMENT 3	0.79***	0.21**	0.66	0.11	0.89	0.34	0.77	0.23	4.3667**	1.1898	2.8575*	0.4573
VEOLIA ENVIRONNEMENT 4	−0.08	1.08***	0.01	0.96	0.04	0.99	0.02	0.98	0.0358	1.2914	0.4692	0.0007
Mean/Ex. rej. at 5% level	0.60	0.40	0.47	0.34	0.66	0.53	0.56	0.44	3	0	1	0

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

the results are virtually the same.[25] The reason may well be found in Fig. 1 which reflects the two alternative LICS series for Alcatel: β equal to 0.56 (Forte (2008)) and β equal to 0.73. It is apparent that the value of β determines the general level of the LICS series, but not its short- or long-term dynamics. Therefore, we conclude that cointegration between LICS series and the other time series is not materially affected by the way that the default point parameter is calibrated in Forte (2008).[26]

To save space, we summarize the credit risk discovery analysis results in Table 12.[27] Overall conclusions are essentially the same as those derived from Table 10. The sole exception might be the somewhat weaker support for the leading role of stocks with respect to bonds in the entire sample period analysis. However, evidence of this pattern of leadership is clearly derived once again from the sub-period analysis.

4.2. Stock returns in a differenced VAR

Previous studies analyze the credit risk discovery process in CDS, bond and stock markets by considering a VAR model for changes in CDS, changes in BS, and stock returns. While the presence of a cointegration relationship between LCDS, LBS and LICS series suggests that such representation is not appropriate (Hasbrouck (1995)), for the sake of completeness it seems suitable to investigate the extent to which the use of ICS series and the more appropriate VECM representation provides additional/different information. We therefore consider the following model:

$$\Delta \mathrm{LCDS}_t = a_1 + \sum_{z=1}^{Z} b_{1z}\Delta \mathrm{LCDS}_{t-z} + \sum_{z=1}^{Z} c_{1z}\Delta \mathrm{LBS}_{t-z} + \sum_{z=1}^{Z} d_{1z}R_{t-z} + \varepsilon_{1t}, \tag{9}$$

$$\Delta \mathrm{LBS}_t = a_2 + \sum_{z=1}^{Z} b_{2z}\Delta \mathrm{LCDS}_{t-z} + \sum_{z=1}^{Z} c_{2z}\Delta \mathrm{LBS}_{t-z} + \sum_{z=1}^{Z} d_{2z}R_{t-z} + \varepsilon_{2t}, \tag{10}$$

$$R_t = a_3 + \sum_{z=1}^{Z} b_{3z}\Delta \mathrm{LCDS}_{t-z} + \sum_{z=1}^{Z} c_{3z}\Delta \mathrm{LBS}_{t-z} + \sum_{z=1}^{Z} d_{3z}R_{t-z} + \varepsilon_{3t}, \tag{11}$$

where R_t stands for stock returns. In testing lead-lag relationships between the different series we employ the same approach already used in Model III (and in previous studies). Table 13 contains specific statistics for companies originally included in Model I. Several conclusions emerge: Firstly, in most cases no significant lead-lag relationship between CDS, BS and stock prices appears. This is evidently the case with BMW although, as a result of price discovery analysis in Section 2, the close connection between markets is made manifest along with the leading role of the stock market. Secondly, for several cases there is a major contradiction in terms of the results obtained using the VECM representation. For example, the VAR model suggests that bonds led CDS in the case of Alcatel (entire sample period analysis, Panel A); however, information shares give the leading edge to the CDS market in this instance (Panel A in Table 6).[28] Despite such contradictions, overall results in Table 14 are

[25] A cointegration relationship between LICS and LCDS is not supported in this setting for Ford Motor Credit Co. when these two series are considered alone (p-value of 0.1179). However, the joint analysis of the three time series again provides clear support for the presence of two independent cointegration equations.

[26] Another illustrative example, the Ford Motor Credit Co. case, can be found in Forte (2008).

[27] A more detailed analysis is available from the authors upon request.

[28] A further investigation on the reasons why the misspecified VAR model may generate conflicting results is beyond the scope of the present study.

Table 9

Model III: Lead-lag relations. This table provides the *F*-statistics that come out from testing, by means of the Wald Test, the null hypothesis that present changes in one given market are independent of past changes in a different market. The number of lags is selected according to the Schwarz criterion for the Entire Sample Period case.

	LCDS vs. LBS		LICS vs. LCDS		LICS vs. LBS	
	Δ LBS/L(Δ LCDS)	Δ LCDS/L(Δ LBS)	Δ LCDS/L(Δ LICS)	Δ LICS/L(Δ LCDS)	Δ LBS/L(Δ LICS)	Δ LICS/L(Δ LBS)
A: Entire sample period						
CARREFOUR	0.0942	2.0896	3.8588*	0.0221	0.4969	0.0008
DAIMLERCHRYSLER	11.6394***	6.1022***	22.5548***	2.6643*	1.9317	3.2484**
DEUTSCHE TELEKOM	4.4020**	0.4356	16.1989***	0.2317	2.3410	0.1801
ENDESA	12.9652***	0.2566	4.4774**	0.0761	0.0512	6.7722***
FRANCE TELECOM	14.5787***	9.4599***	9.1342***	0.0614	14.4348***	0.2128
KPN	21.2408***	22.9574***	1.1724	0.0040	2.0796	0.0534
PHILIPS	0.0058	11.6973***	2.1137	0.0024	1.7161	15.1617***
SIEMENS	0.5354	1.9179	0.0716	0.0596	0.0618	0.7355
VOLKSWAGEN	4.1427**	2.2779	4.4483**	0.3620	0.5994	0.5757
Ex. rej. at 5% level	3	1	5	0	1	3
B: Different sub-periods						
CARREFOUR 1	4.4278**	0.0038	0.4502	0.2868	0.0257	1.0963
CARREFOUR 2	0.4184	0.2428	0.0492	2.7804*	2.8537*	3.1462*
CARREFOUR 3	4.6979**	2.0667	0.0348	0.4291	0.6326	0.0007
CARREFOUR 4	0.5333	1.7310	1.6101	0.0568	0.0003	0.2885
DAIMLERCHRYSLER 1	1.1771	0.5994	7.1225***	0.0090	0.4138	3.1039*
DAIMLERCHRYSLER 2	4.9850***	2.6495*	5.5909***	0.0380	0.7485	0.5184
DAIMLERCHRYSLER 3	6.3585***	6.5053***	6.8392***	2.3216	1.0800	0.1150
DAIMLERCHRYSLER 4	2.1686	1.2511	2.6539*	0.5635	1.5922	1.0577
DEUTSCHE TELEKOM 2	0.0558	0.3561	6.5196**	0.1669	1.0848	0.7601
DEUTSCHE TELEKOM 3	5.7432**	0.5063	2.6625	1.1683	0.4072	0.1001
DEUTSCHE TELEKOM 4	10.1357***	0.6578	9.6276***	0.0302	2.6291	0.4088
ENDESA 1	0.7442	0.1330	1.8487	0.8761	0.1190	1.7673
ENDESA 2	0.3444	0.2831	1.6503	1.8599	1.4387	1.4414
ENDESA 3	0.9609	2.6657	0.0493	2.0121	0.0225	7.1494***
ENDESA 4	0.3640	0.4961	1.9451	0.0700	4.2777**	0.0626
FRANCE TELECOM 1	6.2651**	0.1111	1.9434	1.9872	9.1192***	1.3564
FRANCE TELECOM 2	5.7285**	6.7848**	1.0157	1.3077	0.6093	0.0635
FRANCE TELECOM 3	8.0171***	0.2700	9.6940***	0.9437	2.8770*	1.2240
FRANCE TELECOM 4	0.8981	3.9121*	0.4359	3.9530**	3.7625*	0.0203
KPN 1	0.1270	3.3527*	0.4682	1.2132	0.4321	1.3003
KPN 2	4.3439**	14.0658***	0.7292	1.1762	6.6409**	2.9929*
KPN 3	9.2660***	0.5699	3.2269*	0.0826	1.7422	0.1094
KPN 4	2.4172	0.5706	6.2731**	0.8125	1.3171	0.0757
PHILIPS 1	0.1342	0.5432	0.5897	3.5220*	0.5734	0.0335
PHILIPS 2	0.0039	7.4181***	5.8990**	0.1769	1.8551	5.6459**
PHILIPS 3	0.1397	3.4032*	0.1288	1.0633	5.5073**	4.7547**
PHILIPS 4	0.0819	0.4721	2.4184	0.4813	4.4577**	13.3747***
SIEMENS 1	0.7462	0.1554	0.1188	0.4666	1.1017	0.3714
SIEMENS 2	0.1377	3.3614*	0.2431	0.4597	0.2097	0.2003
SIEMENS 3	0.3666	0.3322	3.9264**	0.8847	0.6627	0.0650
SIEMENS 4	0.7734	0.0030	0.6883	0.7978	0.0118	0.0500
VOLKSWAGEN 2	0.0865	0.1407	0.4977	0.1481	2.8268*	0.0307
VOLKSWAGEN 3	4.9733**	1.5848	2.0643	0.3956	0.0048	0.8214
VOLKSWAGEN 4	0.4809	2.7571*	3.1325*	0.4393	0.0818	0.3478
Ex. rej. at 5% level	9	1	9	1	3	2

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

generally consistent with those derived in Section 2. Notwithstanding, the evidence is much weaker under the VAR representation and reinforces the relevance of considering the more appropriate VECM representation for credit risk discovery analysis.

5. Conclusions

We investigate in this paper the credit risk discovery process in bond, CDS, and stock markets. The analysis is performed on the basis of the credit spread – a homogeneous measure of credit risk for the three markets. Bond and CDS spreads are therefore related to stock market implied credit spreads, which are derived from a modified version of Leland and Toft's (1996) structural credit risk model, together with a novel calibration procedure for determining the model parameters. We argue that, compared with the traditional use of stock returns for credit risk discovery analysis, the application of stock market spreads presents two major advantages: (1) implied credit spreads incorporate information on other relevant variables as the risk-free rate, not merely on stock prices, simultaneously capturing the nonlinear relation between these variables and the credit risk premia; (2) they allow consideration of the long run equilibrium relationships between bond, CDS, and stock market spreads. From a sample of North American and European companies, we conclude that stocks lead CDS and bonds more frequently than the opposite. We also confirm the leading role of the CDS market with respect to the bond market.

Future work should verify the results obtained here, using a larger sample of companies and time periods. Examination of factors underlying the relative contribution of the three markets to price

Table 10

Credit risk discovery. This table summarizes credit risk discovery analysis in Models I, II and III. A dummy variable $D(A,B)$ is defined which takes value 1 if market A headed market B for an specific firm and time period, and 0 otherwise. Both the sum of these dummy variables and their means are reported. The table also includes the Z-statistic testing the null hypothesis of equality of means (different variances).

	CDS vs. bond		Stock vs. CDS		Stock vs. bond	
	D(CDS, Bond)	D(Bond, CDS)	D(Stock, CDS)	D(CDS, Stock)	D(Stock, Bond)	D(Bond, Stock)
A: Entire sample peeriod						
Total	8	3	10	1	7	3
Mean	0.471	0.176	0.588	0.059	0.412	0.176
Z-stat	1.873**		3.881***		1.511*	
(p-value)	(0.031)		(0.000)		(0.065)	
B: Different sub-periods						
Total	23	10	20	5	13	6
Mean	0.383	0.167	0.333	0.083	0.217	0.100
Z-stat	2.716***		3.514***		1.758**	
(p-value)	(0.003)		(0.000)		(0.039)	

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

Table 11

Johansen cointegration Tests. β fixed at 0.73. This table contains Johansen Cointegration Trace Test statistics. The analysis is performed for any possible pair of non-stationary series (Panel A), and for the most general case that accounts the three series simultaneously (Panel B). A constant is allowed both in the cointegration equation and in the VAR component of the VECM. The number of lags is selected according to the Schwarz criterion.

	A						B		
	LCDS–LBS		LICS–LCDS		LICS–LBS		LCDS–LBS–LICS		
	None	At most 1	None	At most 1	None	At most 1	None	At most 1	At most 2
ALCATEL	48.3531***	2.3005	21.0113***	1.4645	20.4738***	0.9683	71.0692***	15.4314*	2.1196
BMW	20.6369***	2.6840	16.1883**	0.8838	21.3753***	1.1691	50.3957***	16.7164**	1.0243
CARREFOUR	6.0088	1.5501	–	–	–	–	–	–	–
DAIMLERCHRYSLER	–	–	–	–	11.4517	1.8220	–	–	–
DEUTSCHE TELEKOM	–	–	8.6040	1.5536	–	–	–	–	–
ENDESA	13.7779*	1.4686	10.2108	1.4753	6.7861	1.3180	22.9712	6.8381	1.5223
FORD MOTOR CREDIT CO.	68.4858***	3.5949*	12.9155	1.7487	29.0096***	1.6361	92.8324***	15.9072**	1.9819
FRANCE TELECOM	10.0350	0.1301	4.5318	0.2939	1.9501	0.2824	19.3601	2.9815	0.0156
GENERAL MOTORS ACCEP.	44.2526***	1.5426	6.8352	0.4230	9.3689	0.3491	50.9749***	7.2697	0.3954
KPN	–	–	–	–	–	–	–	–	–
PHILIPS	16.2705**	2.7091*	7.5862	0.6320	14.4841*	2.3519	25.0561	9.4831	1.9599
PORTUGAL TELECOM	15.3214*	0.2162	7.4816	0.8339	8.2948	0.0117	28.1023*	9.0664	0.0051
ROYAL AHOLD	16.0149**	0.1733	24.8236***	0.0036	10.2565	0.0218	45.7850***	9.1879	0.0117
ROYAL AHOLD (2001–2002)	14.7836*	0.0536	27.1675***	0.0260	15.2934*	0.2395	42.2853***	13.7961*	0.2433
SIEMENS	–	–	8.8397	1.6929	–	–	–	–	–
TELEFONICA	16.9444**	1.9819	10.2479	0.4602	11.9453	0.4985	27.6908*	11.2319	1.9677
VEOLIA ENVIRONNEMENT	49.8649***	2.3103	6.0007	1.3720	5.0722	0.5139	60.0188***	5.5634	0.9120
VOLKSWAGEN	13.2769	2.8152*	10.9884	0.7452	8.0569	0.8896	24.6366	7.9185	0.9721

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

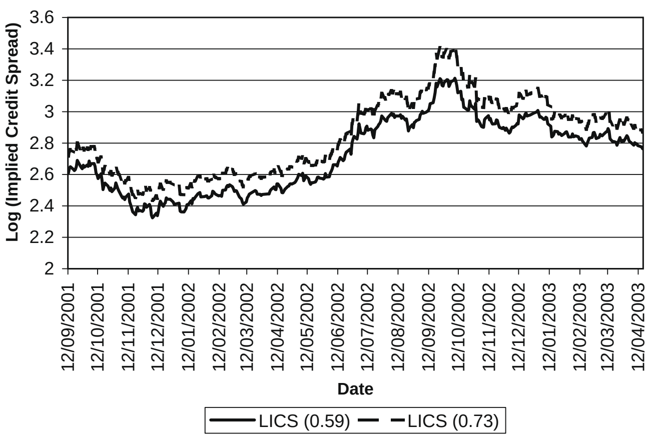

Fig. 1. Alternative LICS series for Alcatel: β equal to 0.59 and β equal to 0.73.

discovery may also be a promising line for future research. A dynamic setting is recommended for this analysis, however, as our estimations indicate some time variation in markets' information shares.

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Table 12
Credit risk discovery. β fixed at 0.73. This table summarizes credit risk discovery analysis in Models I, II and III. A dummy variable $D(A,B)$ is defined which takes value 1 if market A headed market B for an specific firm and time period, and 0 otherwise. Both the sum of these dummy variables and their means are reported. The table also includes the Z-statistic testing the null hypothesis of equality of means (different variances).

	CDS vs. Bond		Stock vs. CDS		Stock vs. Bond	
	D(CDS, Bond)	D(Bond, CDS)	D(Stock, CDS)	D(CDS, Stock)	D(Stock, Bond)	D(Bond, Stock)
A: Entire sample period						
Total	8	3	11	1	6	3
Mean	0.471	0.176	0.647	0.059	0.353	0.176
Z-stat	1.873**		4.417***		1.155	
(*p*-value)	(0.031)		(0.000)		(0.124)	
B: Different sub-periods						
Total	23	10	23	4	15	6
Mean	0.383	0.167	0.383	0.067	0.250	0.100
Z-stat	2.176***		4.451***		2.187**	
(*p*-value)	(0.003)		(0.000)		(0.014)	

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

Table 13
Stock returns in a differenced VAR. Companies originally included in Model I. This table provides the F-statistics that come out from testing, by means of the Wald Test, the null hypothesis that present changes in one given market are independent of past changes in a different market. The number of lags is selected according to the Schwarz criterion for the Entire Sample Period case.

	LCDS vs. LBS		Stocks vs. LCDS		Stocks vs. LBS	
	Δ LBS/L(Δ LCDS)	Δ LCDS/L(Δ LBS)	Δ LCDS/R	R/L(Δ LCDS)	Δ LBS/ R	R/L(Δ LBS)
A: Entire sample period						
ALCATEL	1.2800	11.8428***	1.4963	2.9218*	16.9506***	8.3441***
BMW	0.0014	1.6745	0.3798	0.2296	0.8750	0.4234
FORD MOTOR CREDIT CO.	7.7664***	29.8813***	22.4521***	0.8967	0.1880	18.6206***
ROYAL AHOLD (2001–2002)	4.4462**	4.4641**	1.4293	0.4911	8.1401***	0.3486
B: Different sub-periods						
ALCATEL 1	0.5886	0.0076	1.7342	0.5309	3.9948**	0.1836
ALCATEL 2	0.8519	6.9959***	0.7637	1.4881	2.4519	5.6861**
ALCATEL 3	5.4424**	3.6731*	1.6761	0.6981	4.5134**	5.7159**
ALCATEL 4	23.2335***	0.4107	0.5065	6.0576**	15.3199***	0.5095
BMW 2	0.9000	0.3576	1.0696	0.5570	1.2738	2.4255
BMW 3	3.6867*	2.2579	0.8593	0.1473	0.8390	0.2089
BMW 4	1.8267	0.0807	0.0714	1.6598	0.8307	0.6436
FORD MOTOR CREDIT CO. 1	7.4997***	3.9782*	1.1322	1.1194	0.1518	4.3652**
FORD MOTOR CREDIT CO. 2	8.9487***	1.1157	13.5074***	1.6510	0.4283	0.8775
FORD MOTOR CREDIT CO. 3	8.0188***	22.4050***	1.8601	0.2803	5.1504**	11.8276***
FORD MOTOR CREDIT CO. 4	0.6205	6.3354**	14.5747***	1.5557	0.2516	9.7806***
ROYAL AHOLD 1	0.1349	3.9561*	1.6358	0.1332	0.0324	0.6269
ROYAL AHOLD 2	0.8572	0.0070	0.0166	0.0524	3.1272*	0.0162
ROYAL AHOLD 3	2.1160	2.1229	0.4647	0.3817	3.5395*	0.0624

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

Table 14
Credit risk discovery. Stock returns in a differenced VAR. A dummy variable $D(A,B)$ is defined which takes value 1 if market A headed market B for an specific firm and time period, and 0 otherwise. Both the sum of these dummy variables and their means are reported. The table also includes the Z-statistic testing the null hypothesis of equality of means (different variances).

	CDS vs. Bond		Stock vs. CDS		Stock vs. Bond	
	D(CDS, Bond)	D(Bond, CDS)	D(Stock, CDS)	D(CDS, Stock)	D(Stock, Bond)	D(Bond, Stock)
A: Entire sample period						
Total	4	3	9	0	5	3
Mean	0.235	0.176	0.529	0.000	0.294	0.176
Z-stat	0.413		4.243**		0.792	
(*p*-value)	(0.340)		(0.000)		(0.214)	
B: Different sub-periods						
Total	16	4	12	1	9	4
Mean	0.267	0.067	0.200	0.017	0.150	0.067
Z-stat	3.026**		3.353**		1.470*	
(*p*-value)	(0.001)		(0.000)		(0.071)	

* Indicates significance at the 10% level.
** Indicates significance at the 1% level.

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