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Presented by	**LIDIJA LOVRETA**
Centre	ESADE – ESCUELA SUPERIOR DE ADMINISTRACIÓN Y DIRECCIÓN DE EMPRESAS
Department	MARKETING, OPERATIONS AND FINANCE
Directed by	DR. SANTIAGO FORTE ARCOS

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Introduction

Theory on credit risk valuation provides two main, market-oriented, but conceptually different streams: structural and reduced-form models. Structural models originated from the seminal work of Merton (1974) and were subsequently extended along several dimensions (Black and Cox, 1976; Longstaff and Schwartz, 1995; Leland, 1994; Leland and Toft, 1996, etc.). The fundamental building block of this class of models and the primary source of uncertainty driving credit risk is the firm's asset value dynamics. Corporate securities, debt and equity, are then valued as contingent claims on the underlying firm's asset value assumed to evolve randomly through time with a given expected rate of return and volatility.

A direct implication of these model assumptions is that structural models explicitly link default to the firm's asset value (i.e. default will occur when the firm's asset value becomes insufficient for servicing debt obligations) and provide a direct link between prices of equity and prices of other credit-related instruments (bonds, credit default swaps). Thus, from a theoretical perspective, structural credit risk models are attractive and allow for a broad range of practical application possibilities, such as, for example, extracting information on credit risk from information on stock prices. Their counterparts, reduced-form models, in contrast, lack this explicit endogenous link between default and the firm's asset value and, therefore, cannot be used for certain practical applications that go beyond pricing.

Traditional empirical implementation of structural models in the light of their ability to match market observable levels of credit spreads was not very successful (Jones et al., 1984; Ogden, 1987; Lyden and Saraniti, 2001; Huang and Huang, 2003; Eom et al., 2004). However, theoretical completeness of structural models provoked researchers to focus on overcoming inherent problems of estimation of model parameters, and it turned out that performance of structural models is indeed significantly influenced by employed estimation procedure. Namely, key determinants of default probabilities and credit spreads (firm's asset value, volatility, and default barrier) are pure latent variables. If all liabilities of the firm were traded, estimation of crucial model parameters would be a straightforward task. In practice, this is not the case as only the price of equity, and in some cases a part of the debt, is directly observable.

In the same time, rapid growth of credit derivatives market, a market where credit risk is explicitly traded, provided another measure of credit risk and an attractive benchmark alternative for testing the performance of structural models in addition to traditionally used corporate bond spreads. Credit default swap (CDS), the most liquid credit derivative which provides protection against the credit event by the particular reference entity became a preferable benchmark choice. The buyer of the protection pays a constant fee (i.e. CDS spread) which, by construction, should directly reflect the market perception of credit risk associated with the underlying reference entity (Longstaff, et al., 2005). Nevertheless, the use of CDS spreads as a "pure" credit risk benchmark has been seriously challenged with recent, subprime crisis events, revealing that liquidity should eventually be one of the most important non-default drivers of CDS spreads as suggested in the recent studies of Tang and Yan (2007) and Bongaerts et al. (2010).

This thesis explores the information on credit risk embodied in the stock market and market for credit derivatives (CDS market) on the basis of structural credit risk models. It contains two empirical applications of this class of models that directly stem from the possibility to use structural models to obtain a directly comparable counterpart to CDS spreads - stock market implied credit spreads (ICSs). In addition, the thesis treats the crucial problem of estimation of latent model parameters, contributing to the existing literature by introducing a novel estimation procedure while empirically demonstrating its performance. The specific research questions are discussed further.

The issue addressed in the first chapter refers to relative informational content of stock and CDS market in terms of credit risk. The overall analysis is focused on answering two crucial questions: which of these markets provides more timely information regarding credit risk, and what are the factors that influence informational content of credit risk indicators (i.e. stock market implied credit spreads and CDS spreads). Data set encompasses international set of 94 companies (40 European, 32 US and 22 Japanese) during the period 2002-2004. The main conclusions uncover time-varying behaviour of credit risk discovery, stronger cross market relationship and stock market leadership at higher levels of credit risk, as well as positive relationship between the frequency of severe credit deterioration and the probability of the CDS market leadership.

Second chapter concentrates on the problem of estimation of latent parameters of structural models. It proposes a new, maximum likelihood based iterative algorithm which, on the basis of the log-likelihood function for the time series of equity prices, provides pseudo maximum likelihood estimates of the default barrier and of the value, volatility, and expected return on the firm's assets. The procedure allows for credit risk estimation based only on the readily available information from stock market (i.e. without relying on additional information from other credit-sensitive markets – bond market, or market for credit derivatives). It is demonstrated empirically that, contrary to the standard ML approach, the proposed method ensures that the default barrier always falls within reasonable bounds. Moreover, theoretical credit spreads based on pseudo ML estimates offer the lowest credit default swap pricing errors when compared to the other options that are usually considered when determining the default barrier: standard ML estimate, endogenous value, KMV's default point, and principal value of debt. The obtained results in fact demonstrate that structural models are able to replicate observable CDS spreads quite well.

Final, third chapter, provides further evidence of the performance of the proposed pseudo maximum likelihood procedure and addresses the issue of the presence of non-default components in CDS spreads. Specifically, the effect of demand-supply imbalance, as one important aspect of liquidity in the market where the number of buyers frequently outstrips the number of sellers, is analyzed. The data set is largely extended covering 163 non-financial companies (92 European and 71 North American) and period 2002-2008. In a nutshell, after controlling for the fundamentals reflected through theoretical, stock market implied credit spreads, demand-supply imbalance factors turn out to be important in explaining short-run CDS movements, especially during structural breaks. Results illustrate that CDS spreads reflect not only the price of credit protection, but also a premium for the anticipated cost of unwinding the position of protection sellers.

Chapter 1

Credit Risk Discovery in the Stock and CDS Markets: Who Leads, When, and Why?

1.1 Introduction

Credit risk concerns almost all financial activities and, by definition, should be implicitly or explicitly reflected through market prices of credit sensitive claims, such as credit default swaps (CDSs), bonds and stocks. These assets are traded in structurally different markets, implying probable differences in the relative speed with which respective markets respond to changes in underlying credit conditions. Accordingly, the key issue arises: Which of these markets more rapidly and more efficiently reflects new information regarding credit risk? In an attempt to solve this riddle, recent empirical work has focused primarily on finding *the market* that leads the credit risk price discovery process. This literature suggests that the stock market more often leads the CDS and bond markets than vice versa (Norden and Weber, 2009; Forte and Peña, 2009) and that the CDS market tends to lead the bond market (Longstaff et al., 2003; Blanco et al., 2005; Zhu, 2006; Norden and Weber, 2009; Forte and Peña, 2009).

This empirical evidence has typically been built upon cross-sectional analysis. Several studies suggest, however, that factors underlying credit risk discovery are, in fact, dynamic. There is a well documented positive relationship between the credit quality of a particular company and the liquidity of its stocks (Odders-White and Ready, 2006) and bonds (Longstaff et al., 2005). Furthermore, following the hypothesis of insider trading in credit derivatives, Acharya and Johnson (2007) demonstrate that in days with negative credit news and for companies that experience or are more likely to experience credit deterioration, information flows first into the CDS market and then into the more liquid stock market. In addition, Forte and Peña (2009) provide preliminary evidence that the informational content of CDS, bond, and stock markets, does change over time. In the light of these findings, two natural questions emerge. Are the relative market contributions to credit risk discovery time dependent? If so, what factors influence the relative informational dominance of competing markets? The aim of this chapter is to provide further insight into these basic questions, with a particular focus on the stock and CDS markets.

In undertaking empirical analysis of credit risk discovery that involves stock and CDS markets, it is necessary to cope with the fact that CDS premia and stock prices represent remarkably different credit risk indicators. Market for credit derivatives, as the place where credit risk is explicitly traded, is expected to provide a "pure" measure of credit risk.[1] In contrast, information regarding credit risk is reflected only implicitly through stock prices. As a result of such differences, two approaches for analyzing the credit risk discovery process in respective markets have been proposed. The standard approach (Longstaff et al., 2003; Norden and Weber, 2009) consists of relating stock returns and changes in CDS premia by means of a VAR model. The more recent approach (Forte and Peña, 2009) is based on using information on stock prices, along with a small number of accounting items, to derive the so-called *stock market implied credit spreads* (ICSs) by means of a structural credit risk model. A VECM representation can then be used to relate CDS spreads and ICSs, as these two measures represent alternative proxies for the same latent variable: the pure credit spread.[2]

[1] It may not be the case in practice if non-default components affect CDS premia (e.g. taxes, liquidity). Yet, CDSs are undoubtedly linked directly to the credit quality of the underlying reference entity and, despite its imperfections, are increasingly used in the literature as a directly observable market measure of credit risk (Blanco, et al., 2005; Longstaff et al., 2005; Ericsson et al., 2005)

[2] Such an approach has been regularly applied for investigating the informational content of CDSs and bonds (Blanco et al., 2005; Zhu, 2006; Norden and Weber, 2009)

Compared with the traditional use of stock returns, analysis based on ICSs presents several advantages. Changes in ICSs reflect not only changes in stock prices, but also changes in other variables (e.g. the risk-free rate) all of which are found to be important in determining credit spreads. ICSs also reflect the high non-linearity of the functional relationship between input variables and theoretical credit spreads. Furthermore, the potential long-run equilibrium relationship between stock and CDS markets can be taken into account by means of the corresponding VECM representation.

In this chapter the approach based on ICSs is adopted, providing further evidence for the incremental information conveyed by ICSs in relation to traditionally used stock returns. In line with results provided by Norden and Weber (2009) on the basis of stock returns, it is also shown that the lower the creditworthiness of the reference entity, the stronger the relationship between ICSs and CDS spreads. The sample is taken from Alonso et al. (2008), and consists of CDSs and ICSs for 94 non-financial companies (40 European, 32 US, and 22 Japanese) tracked during the period 2002-2004.[3] Departing from this sample and assuming a time-varying framework, I analyze the credit risk discovery process in the stock and CDS market as well as factors underlying the relative informational dominance of respective markets. To summarize the main results, credit risk discovery in the stock and CDS markets proves to be a dynamic process, with slight informational dominance of the stock market,

[3] The period considered seems to be particularly appropriate for the purposes of this study. It contains both a period of very high (2002-2003) and a period of very low (2003-2004) credit spread levels. Moreover, it avoids the recent financial turmoil when swap rates – the benchmark risk-free rate in credit markets (Blanco et al., 2005; Longstaff et al., 2005; Zhu, 2006) – have lost their traditional highly liquid and risk-free profile. The extent to which swap rates with desirable characteristics are available will directly affect CDS premia and ICS estimates. Although there is no doubt about the interest in extending current analysis to the recent financial crisis, this would not merely require additional data, but would need financial modeling that accounts for both the lack of liquidity and the presence of credit risk in the interbank market as well. The development of such extensions is beyond the scope of this study. The analysis could also benefit from considering the bond market in addition to the stock and CDS markets. This extension, however, would probably be achieved at the cost of a substantial reduction in the number of companies in the final sample. By way of example, there are 18 non-financial companies in Blanco et al. (2005). This is a reasonable reference for the potential number of companies in our sample, as the database on CDS premia in Blanco et al. (2005) is similar to the one in this study. Reduction in the number of companies is usually brought about by the lack of liquid bonds required to generate bond spread series that match the constant maturity of CDS premia (see also Zhu, 2006; Norden and Weber, 2009; and Forte and Peña, 2009).

which declined during the period under consideration. Analysis of factors underlying the relative markets' dominance reveals that the probability of stock market leadership is positively related to the level of credit risk. This result complements rather than contradicts the argument of insider trading in credit derivatives. Specifically, a positive relationship between the frequency of severe credit deterioration shocks and the probability of the CDS market leading credit risk discovery is documented.

The remainder of the chapter is structured as follows. Section 1.2 describes the CDS and ICS database. Section 1.3 addresses the advantages of using ICSs rather than stock returns. Preliminary evidence of a time-varying relationship between CDS spreads and ICSs is also provided. Section 1.4 presents and applies the methodology for credit risk discovery analysis. Section 1.5 examines the factors underlying credit risk discovery in a time-varying context, and Section 1.6 provides the main conclusions.

1.2 Data

1.2.1 Sample selection

The initial data set on CDS spreads and ICSs corresponds to the final sample analyzed by Alonso et al. (2008), and includes 96 non-financial European, US, and Japanese companies, confined to the period 2001-2004. Daily CDS premia (mid bid-ask quotes), obtained from CreditTrade, refer to the close of business in London, New York, and Tokyo.[4] This sample includes only CDS contracts with 5-year maturity that are denominated in local currency: euro-denominated CDSs for 41 companies in the euro area, dollar-denominated CDSs for 32 US companies, and yen-denominated CDSs for 23 Japanese entities.[5]

[4] Blanco et al. (2005), Zhu (2006), and Acharya and Johnson (2007), among others, have previously used the CreditTrade database.

[5] European entities not belonging to the single currency zone are excluded.

Furthermore, each company contains CDS data for at least two consecutive years, with a minimum of 150 observations per year.

Alonso et al. (2008) derive implied credit spreads by considering the modified version of Leland and Toft's (1996) structural credit risk model and the novel calibration methodology proposed by Forte (2008).[6] In a nutshell, the firm asset value and volatility are consistently derived from equity prices, whereas the default barrier is calibrated from CDS premia.[7] Additional inputs to the model are: short- and long-term liabilities, interest expenses, cash dividends, and 1-10 year local swap rates. Daily data on market capitalization (close of business) and 1-10 year local swap rates are obtained from Datastream. Required financial balance-sheet data are gathered from WorldScope.

For comparison, two companies (one European and one Japanese) are excluded from the sample for lack of available credit rating. Data from 2001 is also excluded; CDS series satisfying the inclusion criteria are available for only eight companies in that year. In the first stage of the analysis the entire 2002-2004 sampling period is considered; in the second stage, the entire sample is divided into natural half-yearly periods. Thus, the additional restriction is imposed; no half-yearly period for a company is included unless a minimum of 50 daily CDS-ICS observations is available. The division by natural half-yearly periods seems to be optimal – sufficiently short to capture the dynamics of the factors underlying credit risk discovery and to address the issue of their consequent influence on the informational content

[6] Forte's (2008) calibration methodology has previously been employed for the estimation of the ICS series in Forte and Peña (2009).

[7] A detailed description of the procedure is provided in the Appendix. However, it is worth noting here that the ICS estimations in Alonso et al. (2008) are performed in two steps. In the first step, the default point parameter – the default barrier-to-total debt ratio (DPP) – is assumed to be constant; in the second step, it is allowed to change every year. The data employed in this study follow from the assumption of a constant DPP. This alternative is clearly more appropriate for unit roots tests and cointegration analysis. Please note that these are not the values reported in Alonso et al. (2008), who provide results only from the second step estimation. It is also noteworthy that Forte and Peña (2009) have already shown that using CDSs for the calibration of the DPP does not substantially affect the final results; as long as this parameter remains constant, its value will affect only the general level of the ICS series, but not its short - or long-term dynamics. As a result, price discovery analysis is not materially affected by this value. It is worth nothing that Alonso et al. (2008) introduce the novelty of calibrating bankruptcy costs to reflect the historical recovery rate by sector. Again, this is a constant parameter, implying that no substantial influence on the final results should be expected.

of stock and CDS markets between firm-periods, yet sufficiently long to allow for valid statistical conclusions within each firm-period observation.[8]

In summary, the final sample used in this chapter contains daily data on CDS spreads and ICSs for 94 non-financial companies (40 European, 32 US, and 22 Japanese) tracked from 2 January 2002 to 31 December 2004. For each company, the number of half-yearly periods ranges from 4 to 6. In total, 480 firm-period observations are considered.[9]

1.2.2 Descriptive statistics

General descriptive statistics for CDS spreads and ICS series are depicted in Table 1.1. For the entire sample, CDS spread level ranges around 72 bp, with an evident variation over various periods, ratings, and regions. The mean level of CDS spreads reached its maximum in 2002, with the peak occurring in the second half of the year (approximately 132 bp). Nonetheless, subsequent periods demonstrate a clear downward trend. From the rating perspective, the average level of CDS spreads increases with lower rating categories, whereas the majority of CDS contracts (80.85%) refer to A and BBB rated issuers. Finally, CDS spreads are on average higher for US companies.

Another important characteristic that deserves special attention is the time development of the average bid-ask spread depicted in Figure 1.1. Resembling the mean CDS spread level, the bid-ask spread peaked in the second half of 2002, reaching 23.73 bp on average and thereafter successively declined. As a reference, the last sub-period (second half of the year 2004) examined is characterized by an average bid-ask spread of just 7.94 bp. This patterned time evolution of the bid-ask spread could be associated with the rapid development of the CDS market: more players, increasing competition, higher liquidity, and

[8] Due to the limited number of observations, division by natural quarters would make the econometric analysis questionable. A division on half-yearly periods is also considered in Forte and Peña (2009).
[9] The average number of daily observations is 631 per company and 123 per company-period.

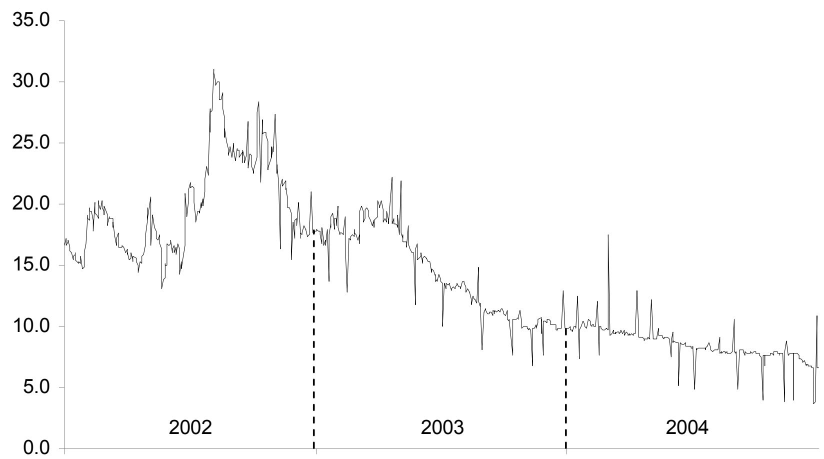
contract standardization. Yet, the mean relative bid-ask spread in Figure 1.2, calculated as a percentage of the mid quote, does not reflect the same tendency.[10]

Table 1.1 *Descriptive Statistics*

Period / Region / Rating	CDS					ICS		
	N firms	Mean	Median	SD	Bid-Ask	Mean	Median	SD
2002	53	109.52	100.51	37.86	20.33	85.33	72.79	45.73
2003	94	74.70	69.29	23.58	14.30	106.93	100.38	38.97
2004	94	51.75	52.81	10.68	8.66	62.85	61.80	16.13
02/1	52	84.81	82.34	17.01	16.70	51.99	47.75	15.49
02/2	53	131.93	134.73	30.64	23.73	115.94	114.22	36.40
03/1	93	92.08	91.59	18.47	17.62	135.36	132.42	28.73
03/2	94	58.76	58.37	10.41	11.33	80.85	79.40	17.91
04/1	94	54.51	54.74	6.64	9.44	59.65	58.86	11.18
04/2	94	49.22	47.92	8.63	7.94	65.88	65.42	11.31
Euro	40	66.12	55.52	31.59	8.85	77.05	62.15	49.95
Dollar	32	101.06	89.21	41.34	20.76	116.82	109.89	52.69
Yen	22	40.45	33.64	20.50	10.48	45.08	34.33	28.60
AAA-AA	14	22.00	19.84	9.35	6.83	24.92	21.18	14.12
A	41	51.39	44.07	23.51	10.84	60.99	52.41	33.82
BBB	35	107.02	90.01	48.45	17.63	121.12	107.78	63.46
BB	4	151.95	145.06	61.75	23.03	180.86	135.04	127.13
All	94	72.00	61.87	32.31	13.29	83.11	71.89	45.89

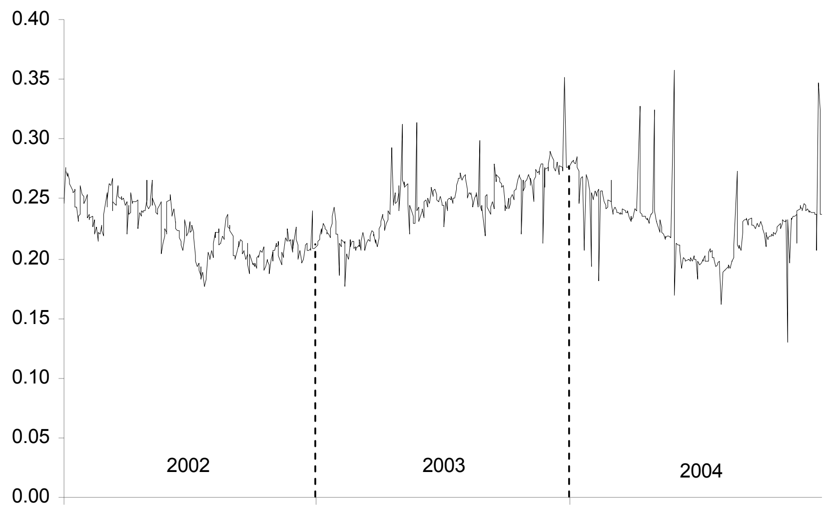
This table provides general descriptive statistics for CDS and ICS series averaged over the period 2002-2004, region, and rating.

Figure 1.1 *Bid-Ask Spread Development over the Period 2002-2004*



[10] Sharp peaks in Figures 1 and 2 occur partly because trading days in the three markets (Europe, US, and Japan) do not match exactly.

Figure 1.2 *Bid-Ask Spread as a Percentage of the Mid-Quote over the Period 2002-2004*



Derived ICS series follow the general pattern observed in the CDS market. For the entire sampling period, the average level of ICSs is around 83 bp, somewhat above the average level of CDS spreads. More formally, Table 1.2 exhibits standard immediate indicators of the pricing discrepancy between the ICS and CDS series: the average basis (*avb*) and the average absolute basis (*avab*). Mean values across all reference entities and periods are 11.1 and 32.85 bp, respectively.[11] These numbers do not deviate appreciably from those in the literature when corporate bond spreads and CDS spreads are compared. Blanco at al. (2005), for example, report an average basis of 6 bp and an average absolute basis of 15 bp; Houweling and Vorst (2005) find an average absolute pricing error of 11 bp. Results in Zhu (2006) are even closer to those in my sample: an average basis of 15 bp and an average absolute basis of 29 bp. Likewise, observed variation across time, rating category, and economic region, is not an unexpected phenomenon. Again, the literature reveals similar patterns in bond and credit default swap spread differentials. As emphasized by Zhu (2006), price discrepancy during volatile periods can be large, while Blanco at al. (2005) find substantial differences between economic regions (US and Europe) and rating categories.

[11] Note that the medians are considerably lower: 4.38 bp for the average basis and 23 bp for the average absolute basis.

Table 1.2 *Credit Spread Differentials between ICS and CDS Series*

Period / Region / Rating		Mean		Median	
	N firms	avb	avab	avb	avab
2002	53	-24.20	46.79	-15.91	32.40
2003	94	32.23	39.60	21.62	24.37
2004	94	11.11	23.32	2.43	12.03
02/1	52	-32.91	42.35	-30.21	32.61
02/2	53	-15.99	51.07	-8.14	38.05
03/1	93	42.97	50.87	29.85	32.94
03/2	94	22.09	28.86	9.64	13.59
04/1	94	5.14	20.05	-0.21	11.36
04/2	94	16.65	26.40	7.73	12.77
Euro	40	10.94	30.99	5.09	22.61
Dollar	32	15.76	45.92	5.94	26.00
Yen	22	4.63	17.20	2.33	12.83
AAA-AA	14	2.92	10.57	2.33	9.64
A	41	9.60	25.40	3.27	20.87
BBB	35	14.10	46.11	8.18	33.02
BB	4	28.91	71.11	23.82	51.61
All	94	11.10	32.85	4.38	23.00

This table provides mean and median values of the standard measures of credit spread differentials between ICS and CDS series: the average basis (*avb)* and the average absolute basis (*avab)*. Measures of discrepancy are reported by period, region, and rating.

1.3 Implied Credit Spreads vs. Stock Returns

As noted in the introduction, the use of stock market implied credit spreads (ICSs) provides several advantages compared to the traditional use of stock returns. Implied credit spreads allow consideration of the eventual long-run equilibrium relationship between the two credit spread series. Likewise, they enable accounting for the effect of other relevant variables in addition to stock prices (e.g. the risk-free rate), while reflecting the highly non-linear functional relationship between considered variables and credit spreads. In order to provide additional support for the argument that ICSs outperform stock returns typically used in the literature, I estimate the following models for changes in CDS spreads.

Model A:

$$\Delta CDS_{i,t} = \alpha_i + \sum_{k=0}^{5} \beta_{i,k} \Delta ICS_{i,t-k} + \sum_{k=1}^{5} \gamma_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}. \tag{1.1}$$

Model B:

$$\Delta CDS_{i,t} = \alpha_i + \sum_{k=0}^{5} \beta_{i,k} R_{i,t-k} + \sum_{k=1}^{5} \gamma_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}. \tag{1.2}$$

In Model A, changes in CDS spreads are regressed on contemporaneous and past changes in ICSs and on past changes in CDS spreads. As a counterpart, Model B takes contemporaneous and past stock returns into account rather than changes in ICSs. Following Acharya and Johnson (2007), the lag length of up to five days is imposed, which seems reasonable for capturing the overall information processing and transmission. Time-series regressions are estimated separately for each company in the sample. Average adj. R^2 statistics, depicted in Table 1.3, undoubtedly show that Model A has higher explanatory power than does Model B: 8.1% for Model A against 7.2% for Model B.[12] These results suggest that ICSs contain certain incremental information as opposed to stock returns.[13]

As a complementary analysis, Model C extends Models A and B by including contemporaneous and past changes in ICSs, along with contemporaneous and past stock returns.

Model C:

$$\Delta CDS_{i,t} = \alpha_i + \sum_{k=0}^{5} \beta_{i,k} \Delta ICS_{i,t-k} + \sum_{k=0}^{5} \rho_{i,k} R_{i,t-k} + \sum_{k=1}^{5} \gamma_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}. \tag{1.3}$$

[12] Reported values are not particularly high, largely because I consider daily data.

[13] I also estimate a model that extends Model B to account for percentage changes in short- and long-term liabilities, interest expenses and cash dividends, and for changes in the 5-year swap rate. Results actually worsen as the adj. R^2 falls to 6.8%.

Table 1.3 *Adjusted R^2 for A, B and C Model Specifications*

Period	N firms	adjusted R^2		
		A	B	C
2002-2004	94	0.081	0.072	0.086

This table provides the average cross-sectional adjusted R^2 statistics from individual time-series regressions for A, B, and C model specifications over the period 2002-2004.

The following alternative hypotheses are tested:

$$H_0 : \rho_{i,k} = 0; k = 0,1, \dots ,5, \tag{1.4}$$

$$H_0 : \beta_{i,k} = 0; k = 0,1, \dots ,5, \tag{1.5}$$

Results, summarized in Table 1.4, indicate that in 25 out of 94 possible cases the null hypothesis that changes in CDS are independent of contemporaneous and past stock returns, is rejected. In contrast, the null hypothesis that changes in CDS are independent of contemporaneous and past changes in ICS is rejected in 41 cases.

Table 1.4 *Hypothesis Testing on Coefficients in Model C*

Period	N firms	H_0: Independence of stock returns		H_0: Independence of changes in ICS	
		Rejections	%	Rejections	%
2002-2004	94	25	26.60%	41	43.62%

This table provides results from testing, in Model C, the null hypothesis that changes in CDS spreads are independent of contemporaneous and past changes in ICSs, and results from testing the null hypothesis that changes in CDS spreads are independent of contemporaneous and past stock returns.

Previous research (Norden and Weber, 2009) suggests not only that the CDS market is sensitive to the stock market, but also that the magnitude of the sensitivity increases with the decrease in the creditworthiness of the reference entity. In order to provide additional evidence on this pattern, I analyze the strength of the relationship between stock and CDS markets by estimating Model A for different half-yearly periods. According to results in

Table 1.5, the explanatory power of the model decreases during the 2002-2004 period, reflecting the change in credit spread levels. More formally, the rank correlation between the adj. R^2 statistic and the average CDS level – computed on a half-yearly basis and for the total sample of 480 firm-period observations – equals 0.45, and is statistically significant at the 1% level. The intersection by credit rating group leads to the same conclusion; the explanatory power evidently rises when moving from AAA-AA to BBB rating group.[14] Overall, these results support the idea of a time-varying relationship between stock and CDS markets.

Table 1.5 *Explanatory Power and Credit Risk Level*

Period / Rating	N firms	Model A adj R^2	Mean CDS level	Median CDS level
2002	53	0.121	109.52	100.51
2003	94	0.076	74.70	69.29
2004	94	0.044	51.75	52.81
02/1	52	0.100	84.81	82.34
02/2	53	0.111	131.93	134.73
03/1	93	0.075	92.08	91.59
03/2	94	0.049	58.76	58.37
04/1	94	0.047	54.51	54.74
04/2	94	0.032	49.22	47.92
AAA-AA	14	0.042	22.00	19.84
A	41	0.089	51.39	44.07
BBB	35	0.094	107.02	90.01
BB	4	0.036	151.95	145.06
All	94	0.081	72.00	61.87

This table provides adjusted R^2 statistics for Model A over the period 2002-2004 and over different rating categories, together with the corresponding mean and median levels of CDS spreads.

[14] The BB rating group includes only four companies, not allowing for valid conclusions.

1.4 Credit Risk Discovery

1.4.1 Cointegration analysis

Provided that stock and CDS markets price credit risk equally in the long-run, and as long as factors that differ from credit risk (e.g. liquidity considerations, measurement errors) do not affect ICS and CDS time series on a permanent basis, the two credit spread series should be cointegrated. At the same time, the common factor could be thought of as the implicit, unobservable efficient price of credit risk.

We start by performing Augmented Dickey-Fuller (ADF) Tests for the presence of unit roots, where the corresponding number of lags is selected according to the Akaike Information Criterion. Results in Table 1.6 show that the null hypothesis – the level of the time series is non-stationary – is rejected at the 95% level for 26 companies in the case of CDS series and for 11 companies in the case of ICS series. Significant evidence of unit roots in both series is detected for 66 companies. In order to examine the eventual existence of cointegration between those ICS and CDS time series that simultaneously prove to be I(1), VAR-based Johansen Cointegration Test is applied.[15] As indicated in Table 1.7, clear evidence of a cointegration relationship is found for 17 firms; for these entities it can be concluded that ICSs and CDS spreads are driven, in the long-run, by the same common factor.

[15] According to Engle and Granger (1987), if two time series have unit roots, then their linear combination may be stationary. If this is the case, series are said to be cointegrated, where cointegrating equations may be understood as a long-run equilibrium relationship.

Table 1.6 *Augmented Dickey-Fuller (ADF) Tests*

Panel A

Company ID	Company Name	CDS		ICS	
		t-stat	p-val	*t*-stat	p-val
3	BASF AG	-3.750	0.020 **	-0.980	0.293
6	BOUYGUES SA	-3.187	0.002 ***	-3.779	0.018 **
8	DAIMLERCHRYSLER AG	-4.110	0.006 ***	-0.500	0.499
11	ELECTRICIDADE DE PORTUGAL SA	-2.431	0.015 **	-1.529	0.119
18	KONINKLIJKE KPN NV	-1.480	0.130	-2.017	0.042 **
26	SAINT GOBAIN	-3.976	0.000 ***	-2.854	0.004 ***
28	STMICROELECTRONICS NV	-3.335	0.001 ***	-0.467	0.513
32	THALES SA	-3.618	0.000 ***	-0.898	0.327
33	THYSSENKRUPP AG	-5.210	0.000 ***	-1.018	0.278
36	VALEO SA	-3.021	0.034 **	-2.719	0.229
45	CENTEX CORP	-2.971	0.039 **	-1.373	0.158
61	NORTHROP GRUMMAN CORP	-1.020	0.277	-2.352	0.018 **
62	OMNICOM GROUP	-2.763	0.006 ***	-0.961	0.301
68	TOYS R US INC	-3.521	0.038 **	-2.419	0.137
72	WALT DISNEY CO, THE	-2.368	0.017 **	-4.361	0.000 ***
74	CANON INC	-2.666	0.008 ***	-1.581	0.107
78	HITACHI LTD	-1.963	0.048 **	-1.869	0.347
79	HONDA MOTOR CO LTD	-27.033	0.000 ***	0.000	0.683
81	JAPAN TOBACCO INC	-3.859	0.015 **	-4.046	0.008 ***
83	MATSUSHITA ELECTRIC INDUSTRIAL CO LTD	-2.635	0.008 ***	-1.157	0.226
84	MITSUBISHI CORP	-2.952	0.003 ***	-2.096	0.035 **
85	MITSUI AND CO LTD	-3.343	0.014 **	-2.753	0.006 ***
86	NEC CORP	-3.941	0.000 ***	-2.358	0.018 **
87	NIPPON STEEL CORP	-3.587	0.000 ***	-2.389	0.017 **
88	NIPPON TELEGRAPH AND TELEPHONE CORP	-3.741	0.000 ***	-1.569	0.110
89	NTT DOCOMO INC	-4.128	0.000 ***	-0.416	0.533
92	SUMITOMO CORP	-4.670	0.000 ***	-2.049	0.039 **
94	TOSHIBA CORP	-2.049	0.039 **	-1.111	0.242

ADF unit root tests are performed for the three possible alternatives: without constant and trend in the series, with constant and without trend, and with constant and trend. Reported ADF test statistics correspond to the model with the lowest Schwarz Information Criterion, where the number of lags is determined according to the Akaike Information Criterion. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Panel A lists the companies for which the presence of unit roots is rejected at the 95% level for at least one series. Panel B lists the companies for which the ADF test shows I(1) for both series simultaneously.

Panel B

Company ID	Company Name	CDS		ICS	
		t-stat	p-val	*t*-stat	p-val
1	AKZO NOBEL NV	-0.734	0.398	-0.830	0.356
2	ARCELOR	-1.154	0.227	-0.929	0.314
4	BAYER AG	-1.317	0.174	-1.313	0.175
5	BMW AG	-0.721	0.405	-0.316	0.572
7	CARREFOUR SA	-0.788	0.375	-0.178	0.622
9	DEUTSCHE LUFTHANSA AG	-1.300	0.179	-0.590	0.462
10	E.ON AG	-0.646	0.437	-0.643	0.439
12	ENDESA	-1.187	0.216	-1.127	0.237
13	ENEL SPA	-0.715	0.407	-0.695	0.416
14	ENI SPA	-1.128	0.236	-0.860	0.343
15	FINMECCANICA SPA	-0.551	0.478	-2.677	0.079 *
16	FRANCE TELECOM	-0.809	0.366	-0.952	0.304
17	HEIDELBERGCEMENT AG	-0.599	0.458	-1.042	0.268
19	KONINKLIJKE PHILIPS ELECTRONICS NV	-1.032	0.272	-0.546	0.481
20	L AIR LIQUIDE SA	-0.977	0.294	1.229	0.944
21	METRO AG	-0.814	0.363	-1.355	0.163
22	NOKIA OYJ	-0.819	0.361	-0.267	0.590
23	PEUGEOT SA	-2.986	0.137	-0.475	0.510
24	RENAULT SA	-1.506	0.124	-1.395	0.152
25	RWE AG	-0.774	0.381	-0.985	0.291
27	SIEMENS AG	-0.826	0.358	-1.124	0.238
29	STORA ENSO OYJ	-1.022	0.276	-2.810	0.057 *
30	SUEZ SA	-0.817	0.362	-1.084	0.253
31	TELEFONICA SA	-1.009	0.281	-1.142	0.231
34	TOTALFINAELF SA	-1.031	0.273	-0.488	0.505
35	UPM-KYMMENE OYJ	-0.798	0.370	-2.060	0.261
37	VEOLIA ENVIRONNEMENT	-1.693	0.086 *	-1.849	0.062 *
38	VNU NV	-1.290	0.182	-0.891	0.330
39	VOLKSWAGEN AG	-2.851	0.052 *	0.668	0.860
40	WOLTERS KLUWER NV	-1.027	0.274	-0.883	0.334
41	ALBERTSONS INC	-1.286	0.183	-0.702	0.412
42	BELLSOUTH CORPORATION	-1.213	0.207	-0.672	0.426
43	BOEING CO	-1.085	0.252	-0.705	0.411
44	CATERPILLAR INC	-1.885	0.057 *	-1.209	0.208
46	CVS CORP	-1.669	0.090 *	-1.744	0.409
47	DEERE AND CO	-1.370	0.159	-0.986	0.291
48	DELL COMPUTER CORP	-1.535	0.117	-0.347	0.560
49	DELPHI CORP	-0.332	0.566	0.117	0.719
50	DOW CHEMICAL CO, THE	-1.006	0.283	-0.790	0.374
51	EASTMAN KODAK CO	-1.292	0.182	-0.924	0.316
52	ELECTRONIC DATA SYSTEMS CORP	-1.037	0.270	-0.944	0.307
53	FEDERATED DEPARTMENT STORES INC	-1.202	0.211	-0.863	0.342
54	FORD MOTOR CREDIT CO	-0.711	0.409	-1.747	0.407
55	GENERAL ELECTRIC CAPITAL CORP	-0.621	0.448	-0.503	0.499
56	GENERAL MOTORS ACCEPTANCE CORP	-2.315	0.168	0.392	0.797
57	MAY DEPARTMENT STORES CO	-2.761	0.065 *	-1.492	0.127
58	MAYTAG CORP	0.836	0.891	-0.329	0.567
59	NORDSTROM INC	-1.563	0.111	-1.770	0.073 *
60	NORFOLK SOUTHERN CORP	-1.072	0.257	-1.005	0.283
63	SBC COMMUNICATIONS INC	-1.196	0.213	-3.138	0.098 *
64	SOUTHWEST AIRLINES CO	-1.124	0.237	-0.327	0.568
65	SPRINT CORP	-1.002	0.284	-0.911	0.322
66	SUN MICROSYSTEMS INC	-0.948	0.306	-2.585	0.097 *
67	TARGET CORP	-0.772	0.382	-0.707	0.411
69	VERIZON GLOBAL FUNDING CORP	-1.279	0.186	-0.884	0.333
70	VIACOM INC	-1.574	0.109	-0.459	0.516
71	VISTEON CORP	-2.546	0.105	-0.446	0.521
73	ALL NIPPON AIRWAYS CO LTD	-1.255	0.193	-1.769	0.073 *
75	CHUBU ELECTRIC POWER CO INC	-1.591	0.105	-1.342	0.167
76	DAIWA SECURITIES GROUP INC	-1.529	0.119	-0.905	0.324
77	FUJITSU LTD	-1.123	0.238	-0.595	0.459
80	JAPAN AIRLINES SYSTEM CORP	-1.318	0.622	-1.158	0.225
82	KANSAI ELECTRIC POWER CO INC	-1.339	0.168	-1.244	0.197
90	SHARP CORP	-3.166	0.092 *	-0.744	0.394
91	SONY CORP	-1.644	0.095 *	-0.258	0.593
93	TOKYO ELECTRIC POWER CO INC	-1.088	0.251	-0.785	0.376

Table 1.7 *Johansen Cointegration Tests*

Company ID	Company Name	None	At most 1
		Trace stat	Trace stat
1	AKZO NOBEL NV	10.565	1.227
2	ARCELOR	13.059	0.787
4	BAYER AG	19.517 **	2.863 *
5	BMW AG	9.889	3.134 *
7	CARREFOUR SA	12.749	3.197 *
9	DEUTSCHE LUFTHANSA AG	9.380	2.507
10	E.ON AG	12.661	1.910
12	ENDESA	37.630 ***	2.801 *
13	ENEL SPA	11.535	2.000
14	ENI SPA	7.904	3.206 *
15	FINMECCANICA SPA	10.035	2.126
16	FRANCE TELECOM	11.353	0.863
17	HEIDELBERGCEMENT AG	9.551	1.333
19	KONINKLIJKE PHILIPS ELECTRONICS NV	9.112	1.267
20	L AIR LIQUIDE SA	5.494	0.051
21	METRO AG	23.970 ***	3.623 *
22	NOKIA OYJ	7.498	0.671
23	PEUGEOT SA	10.220	3.731 *
24	RENAULT SA	10.154	2.699
25	RWE AG	10.522	3.321 *
27	SIEMENS AG	8.464	1.683
29	STORA ENSO OYJ	16.789 **	1.764
30	SUEZ SA	8.879	2.927 *
31	TELEFONICA SA	21.642 ***	1.779
34	TOTALFINAELF SA	9.729	2.926 *
35	UPM-KYMMENE OYJ	8.397	1.632
37	VEOLIA ENVIRONNEMENT	9.554	0.784
38	VNU NV	31.924 ***	3.260 *
39	VOLKSWAGEN AG	12.748	2.220
40	WOLTERS KLUWER NV	8.071	3.701 *
41	ALBERTSONS INC	7.761	1.542
42	BELLSOUTH CORPORATION	21.997 ***	2.505
43	BOEING CO	13.081	1.780
44	CATERPILLAR INC	23.051 ***	2.018
46	CVS CORP	10.796 *	2.804
47	DEERE AND CO	7.211	2.170
48	DELL COMPUTER CORP	10.386	2.957 *
49	DELPHI CORP	10.705	2.370
50	DOW CHEMICAL CO, THE	22.571 ***	0.821
51	EASTMAN KODAK CO	14.312 *	1.007
52	ELECTRONIC DATA SYSTEMS CORP	18.991 **	1.055
53	FEDERATED DEPARTMENT STORES INC	7.517	2.210
54	FORD MOTOR CREDIT CO	14.186 *	2.659
55	GENERAL ELECTRIC CAPITAL CORP	10.191	1.779
56	GENERAL MOTORS ACCEPTANCE CORP	8.773	2.793 *
57	MAY DEPARTMENT STORES CO	17.984 **	1.039
58	MAYTAG CORP	11.085	0.372
59	NORDSTROM INC	14.425 *	1.960
60	NORFOLK SOUTHERN CORP	5.497	0.658
63	SBC COMMUNICATIONS INC	15.497 *	0.633
64	SOUTHWEST AIRLINES CO	8.779	3.697 *
65	SPRINT CORP	19.822 **	1.238
66	SUN MICROSYSTEMS INC	12.356	2.672
67	TARGET CORP	14.410 *	2.454
69	VERIZON GLOBAL FUNDING CORP	12.842	1.886
70	VIACOM INC	9.587	2.640
71	VISTEON CORP	39.264 ***	2.557
73	ALL NIPPON AIRWAYS CO LTD	13.284	1.884
75	CHUBU ELECTRIC POWER CO INC	11.626	0.308
76	DAIWA SECURITIES GROUP INC	6.587	0.652
77	FUJITSU LTD	17.922 **	1.125
80	JAPAN AIRLINES SYSTEM CORP	11.895	1.243
82	KANSAI ELECTRIC POWER CO INC	19.272 **	0.352
90	SHARP CORP	10.296	2.389
91	SONY CORP	16.284 **	3.203 *
93	TOKYO ELECTRIC POWER CO INC	15.892 **	1.310

Johansen Cointegration Tests are performed for the 66 pairs of non-stationary ICS – CDS series. A constant is allowed both in the cointegration equation and in the VAR component of the VECM, whereas the number of lags is determined according to the Schwarz Information Criterion. Reported Trace Statistics correspond to the number of cointegration relationships between ICS and CDS series. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

In the presence of cointegration, the short-term dynamics between CDS spreads and ICSs is characterized by a VECM representation. Accordingly, the following two-dimensional VECM is specified for the respective 17 companies:

$$\Delta ICS_t = \alpha_1 + \lambda_1(ICS_{t-1} - \delta_0 - \delta_1 CDS_{t-1}) + \sum_{j=1}^{p} \beta_{1j} \Delta ICS_{t-j} + \sum_{j=1}^{5} \gamma_{1j} \Delta CDS_{t-j} + \varepsilon_{1t} \quad (1.6)$$

$$\Delta CDS_t = \alpha_2 + \lambda_2(ICS_{t-1} - \delta_0 - \delta_1 CDS_{t-1}) + \sum_{j=1}^{p} \beta_{2j} \Delta ICS_{t-j} + \sum_{j=1}^{5} \gamma_{2j} \Delta CDS_{t-j} + \varepsilon_{2t} \quad (1.7)$$

where, ε_1 and ε_2 are i.i.d. error terms, and the lag length p is determined according to the Schwarz Information Criterion. Loadings λ_1 and λ_2 represent the adjustment coefficients that measure the speed with which CDS spreads and ICSs adjust to eliminate 'pricing errors' – deviations from the long-run equilibrium. If λ_1 is significantly negative, then ICSs adjust to eliminate pricing errors. A significantly positive λ_2 implies, on the other hand, that CDS spreads adjust to eliminate pricing errors. If both coefficients are significant – and correctly signed – then both markets contribute to price discovery; their relative magnitude will determine which of these markets more rapidly absorbs and reflects new information about changes in the credit conditions of the underlying reference entity.

Estimated λ_1 and λ_2 coefficients are presented in Table 1.8. For each firm there is at least one significant loading coefficient. Of the 17 entities, λ_1 is significantly negative at the 5% level for 11 names (ICSs adjust). The contrary effect (CDS spreads adjust), expressed through a significantly positive $\lambda_{2,}$ is supported for 12 companies. Moreover, strong one-way price adjustments of the CDS market to the stock market is evident in 6 cases; the reverse holds for 5 cases. Both coefficients are correctly signed and significant in 6 cases. At first glance, and according to the significance and correctly signed factor loadings, it seems that both markets contribute almost equally to price discovery.

Table 1.8 *Measures of Contribution to Price Discovery*

Company Name	λ_1	*t*-stat	λ_2	*t*-stat	GG	Hasbrouck Lower	Hasbrouck Upper	Hasbrouck Mid
BAYER AG	0.013	0.600	0.078	4.061 ***	1.20	0.98	0.99	0.98
ENDESA	-0.041	-3.379 ***	0.032	4.257 ***	0.43	0.51	0.68	0.59
METRO AG	0.002	0.157	0.018	4.400 ***	1.11	0.95	1.00	0.97
STORA ENSO OYJ	-0.016	-2.261 **	0.007	2.039 **	0.30	0.39	0.52	0.46
TELEFONICA SA	-0.022	-1.984 **	0.021	2.894 ***	0.49	0.42	0.80	0.61
VNU NV	-0.040	-3.167 ***	0.009	0.773	0.18	0.05	0.20	0.12
BELLSOUTH CORPORATION	-0.046	-3.684 ***	-0.015	-2.595 ***	-0.46	0.31	0.34	0.33
CATERPILLAR INC	-0.007	-1.359 *	0.009	3.514 ***	0.57	0.77	0.89	0.83
DOW CHEMICAL CO	-0.038	-2.936 ***	0.034	3.245 ***	0.48	0.48	0.61	0.54
ELECTRONIC DATA SYSTEMS CORP	-0.004	-0.402	0.041	4.085 ***	0.92	0.92	0.99	0.96
MAY DEPARTMENT STORES CO	-0.014	-1.947 *	0.010	2.904 ***	0.41	0.69	0.69	0.69
SPRINT CORP	-0.044	-3.280 ***	0.019	0.829	0.29	0.04	0.43	0.23
VISTEON CORP	-0.002	-0.158	0.053	6.094 ***	0.97	0.98	1.00	0.99
FUJITSU LTD	-0.009	-2.489 **	0.029	3.093 ***	0.76	0.57	0.63	0.60
KANSAI ELECTRIC POWER CO INC	-0.038	-3.975 ***	0.009	1.859 *	0.18	0.17	0.18	0.18
SONY CORP	-0.018	-3.357 ***	-0.005	-1.748 *	-0.40	0.14	0.23	0.19
TOKYO ELECTRIC POWER CO INC	-0.029	-3.780 ***	0.003	0.464	0.10	0.01	0.02	0.02
Average					0.48	0.49	0.60	0.55

This table reports alternative measures of the stock and CDS market contribution to price discovery (λ_1, λ_2, GG, and Hasbrouck measures) for the companies for which a cointegration relationship has been detected. Estimated λ_1 and λ_2 coefficients are presented, along with the corresponding *t*-values. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

More formally, Gonzalo and Granger (1995), and Hasbrouck (1995), introduced two alternative measures of a single market contribution to price discovery. Gonzalo and Granger's (GG) measure is based on the ratio between the two factor loadings, defined as

$$GG = \frac{\lambda_2}{\lambda_2 - \lambda_1}. \tag{1.8}$$

In the particular case analyzed in this chapter, the higher the GG measure, the higher the stock market contribution (the lower the CDS market contribution) to price discovery. Nevertheless, the GG measure may sometimes exceed 1 or be below 0. If GG $\geq$ 1, then the stock market clearly dominates the CDS market in price discovery. For GG $\leq$ 1 the inverse situation holds. In the case of the 17 examined entities, the GG measure supports CDS market leadership for 11 companies, whereas the reverse appears to be true for only six companies. Furthermore, the average GG measure for all the companies considered is 0.48, suggesting a slight dominance of the CDS market in price discovery during the entire 2002-2004 sample period.[16]

Alternatively, Hasbrouck (1995) proposed the model of *information shares*, which assumes that the market that contributes more to the variance of innovations in the implicit unobservable efficient price (i.e. the common factor implied by cointegration) is informationally dominant and contributes more to price discovery. The information share of a given market is therefore determined by the proportion of the innovation variance that can be attributed to that market. When innovations are correlated, Hasbrouck suggests lower (HL) and upper (HU) limits for market shares:

$$HL = \frac{\lambda_2^2\left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}\ ; \qquad HU = \frac{\left(\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}\ ; \tag{1.9}$$

where σ_1, σ_2, and σ_{12}, are the elements of the variance-covariance matrix of the residuals from the VECM specification. The mid-Hasbrouck measure (HM), calculated at the midpoint of the lower and upper bound, is usually taken as an adequate measure of a single market contribution to price discovery (Baillie et al, 2002). According to this measure, the stock market dominates in 10 cases, the CDS market dominates in 7 cases, and the average for all the entities examined amounts to 0.55, signifying a slight dominance of the stock market in price discovery.

Contrasting average GG and HM measures over the entire sampling period implies that both markets contribute approximately equally to price discovery; both measures are close to 0.5, and no clear conclusion can be made regarding which of the markets is more informationally efficient. Repeating the same exercise in a time-varying context, however, provides a more detailed picture of the price discovery process. Half-yearly loadings for each

[16] In the calculation of the average GG measure, values above 1 and below 0 are set to 1 and 0, respectively.

company and period, reported in Table 1.9, are estimated by imposing the entire sample cointegrating vector to the restricted time intervals. As for the entire sample, the analysis reveals no leadership concentration in either of the markets; however, it does reveal a downward trend in the information share of the stock market with respect to the CDS market. At the beginning of the sampling period (first half of 2002), the HM (GG) measure for the information share of the stock market was relatively high: approximately 0.67 (0.63). A much smaller proportion of price discovery can be attributed to this market, however, in the second half of 2004: approximately 0.46 (0.37).

Table 1.9 *Measures of Contribution to Price Discovery over Half-Yearly Periods*

Period	N firms	GG	Hasbrouck		
			Lower	Upper	Mid
02/1	12	0.63	0.61	0.72	0.67
02/2	12	0.49	0.44	0.63	0.54
03/1	17	0.41	0.43	0.56	0.50
03/2	17	0.43	0.43	0.51	0.47
04/1	17	0.43	0.52	0.59	0.56
04/2	17	0.37	0.44	0.50	0.46
All	92	0.46	0.48	0.59	0.53

This table reports GG and Hasbrouck measures of the stock and CDS market contribution to price discovery process over the corresponding half-yearly periods. For the sake of brevity, the table presents only the mean level of the individual values estimated for the companies for which the cointegration relationship has been detected by the Johansen Cointegration Test over the entire sample period. Half-yearly coefficients are estimated by imposing the entire sample cointegration equation on the half-yearly VECM.

1.4.2. Granger causality

For the sub-sample of 77 entities that either do not have unit roots, or for which the cointegration is rejected, the VECM approach is not valid. Price leadership is tested in these cases by the presence of Granger causality in a VAR model of the form:

$$\Delta ICS_t = \alpha_1 + \sum_{j=1}^{p} \beta_{1j} \Delta ICS_{t-j} + \sum_{j=1}^{5} \gamma_{1j} \Delta CDS_{t-j} + \varepsilon_{1t}\,, \qquad (1.10)$$

$$\Delta CDS_t = \alpha_2 + \sum_{j=1}^{p} \beta_{2j} \Delta ICS_{t-j} + \sum_{j=1}^{5} \gamma_{2j} \Delta CDS_{t-j} + \varepsilon_{2t} , \tag{1.11}$$

where ε_1 and ε_2 are i.i.d. error terms, and p is the number of lags determined according to the Schwarz Information Criterion. The Granger Causality Test is not aimed at revealing the causality pattern between the considered series, but does yield information regarding the price formation dynamics and information precedence. It actually tests whether coefficients of the lagged changes in CDS spread levels are statistically significant, and help in the explanation of the current changes in ICSs (and vice versa).

F-statistics for the corresponding Wald Tests are presented in Table 1.10. The null hypothesis that changes in ICSs do not Granger-cause changes in CDS spreads is rejected at the 95% significance level for 47 companies (61.04% of the sub-sample of 77 names). In contrast, the null hypothesis that changes in CDS spreads do not Granger-cause changes in ICSs is rejected for only 16 companies (20.78%). Furthermore, a one-way influence of the stock market (ΔICS do Granger-cause ΔCDS, but ΔCDS do not Granger-cause ΔICS) is detected for 36 companies, whereas the opposite is true just for 5 entities. Overall, it seems that lagged changes in ICSs are important in explaining current changes in CDS spreads more often than the other way around, which may suggest the dominance of the stock market in credit risk discovery over the entire 2002-2004 sampling period. These results are not surprising; the literature has already uncovered similar patterns when considering stock returns (Norden and Weber, 2009).[17]

[17] See also Forte and Peña (2009).

Table 1.10 *Granger Causality Tests*

Company Name	∆ICS dngc ∆CDS *F*-statistic		∆CDS dngc ∆ICS *F*-statistic	
AKZO NOBEL NV	7.564	***	0.180	
ARCELOR	4.215	**	1.725	
BMW AG	4.119	**	10.870	***
CARREFOUR SA	18.914	***	1.431	
DAIMLERCHRYSLER AG	25.560	***	0.473	
DEUTSCHE LUFTHANSA AG	30.926	***	3.454	*
E.ON AG	14.411	***	0.884	
ELECTRICIDADE DE PORTUGAL SA	6.580	**	0.176	
FINMECCANICA SPA	15.223	***	0.153	
FRANCE TELECOM	23.229	***	2.849	*
HEIDELBERGCEMENT AG	3.944	**	0.931	
KONINKLIJKE KPN NV	25.340	***	4.818	**
KONINKLIJKE PHILIPS ELECTRONICS NV	5.600	**	2.824	*
L AIR LIQUIDE SA	0.700		5.373	**
NOKIA OYJ	10.546	***	1.314	
PEUGEOT SA	21.850	***	1.920	
RENAULT SA	11.141	***	0.210	
RWE AG	28.656	***	0.445	
SAINT GOBAIN	4.115	***	6.067	***
SIEMENS AG	46.190	***	0.000	
STMICROELECTRONICS NV	4.446	**	1.022	
SUEZ SA	18.314	***	0.359	
THALES SA	5.326	**	0.461	
THYSSENKRUPP AG	1.471		21.046	***
VALEO SA	9.868	***	19.096	***
VOLKSWAGEN AG	36.913	***	1.107	
BOEING CO	19.885	***	10.075	***
DEERE AND CO	4.075	**	4.092	**
EASTMAN KODAK CO	62.310	***	0.002	
FEDERATED DEPARTMENT STORES INC	37.829	***	0.004	
FORD MOTOR CREDIT CO	95.236	***	0.362	
GENERAL ELECTRIC CAPITAL CORP	15.567	***	0.532	
GENERAL MOTORS ACCEPTANCE CORP	25.942	***	0.045	
MAYTAG CORP	10.853	***	5.288	**
NORDSTROM INC	4.201	**	0.319	
NORFOLK SOUTHERN CORP	6.805	***	1.693	
NORTHROP GRUMMAN CORP	1.659		3.002	***
SBC COMMUNICATIONS INC	10.280	***	3.357	*
SUN MICROSYSTEMS INC	19.407	***	0.023	
TARGET CORP	28.335	***	5.073	**
TOYS R US INC	7.346	***	1.614	
VERIZON GLOBAL FUNDING CORP	22.789	***	5.586	***
WALT DISNEY CO, THE	10.619	***	0.035	
DAIWA SECURITIES GROUP INC	4.552	**	4.773	**
HITACHI LTD	5.745	***	0.300	
JAPAN AIRLINES SYSTEM CORP	1.982	*	3.754	***
MATSUSHITA ELECTRIC INDUSTRIAL CO LTD	8.039	***	2.747	*
NIPPON STEEL CORP	1.002		2.788	**
NIPPON TELEGRAPH AND TELEPHONE CORP	8.625	***	2.423	
NTT DOCOMO INC	2.830	**	2.390	*
SHARP CORP	6.235	**	4.975	**
TOSHIBA CORP	6.521	**	2.464	

The table reports pairwise Granger Causality Test statistics (dngc = does not Granger cause) for the sub-sample of 77 companies that either a) do not have unit roots or b) the cointegration relationship is not distinctly suggested by the Johansen Cointegration Test. The number of lags is selected according to the Schwarz Information Criterion. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

In order to determine if these findings are stable over time, I perform the same analysis by natural half-yearly periods; Results are presented in Table 1.11. Again, the null hypothesis – ΔICS do not Granger-cause ΔCDS – is rejected more frequently than vice versa. The informational precedence of the stock market, however, appears to diminish over the period considered (measured by the proportion of the null hypothesis rejections in the total number of examined companies), in line with results from the VECM analysis.

Table 1.11 *Granger Causality Tests over Half-Yearly Periods*

Period	N firms	ΔICS dgc ΔCDS		ΔCDS dgc ΔICS	
		N firms	%	N firms	%
02/1	40	13	32.50	3	7.50
02/2	41	18	43.90	1	2.44
03/1	76	20	26.32	10	13.16
03/2	77	14	18.18	7	9.09
04/1	77	14	18.18	5	6.49
04/2	77	12	15.58	7	9.09
All	388	91	23.45	33	8.5

The table reports the number and percentage of firms for which the corresponding Granger Causality Test statistic is significant at the 5% level, over each of the considered half-yearly periods.

1.5 Factors Underlying Credit Risk Discovery

In this section, I extend previous analysis by investigating factors that may influence the informational dominance of the stock and CDS markets. As it has been shown, the relative contribution of these markets to credit risk discovery differs not only between companies, but also within the same company across different periods. Thus, I depart from results obtained in the analysis of half-yearly periods. Regarding potential factors, and in the light of the existing literature and my own findings, I consider the following: liquidity of the CDS and stock markets, credit quality of the reference entity, presence of significant negative shocks, and time period. A detailed description follows.

CDS percentage bid-ask spread. Liquidity is an obscure concept and there is no one, universally accepted liquidity measure. The literature has considered many different alternatives, with the percentage bid-ask spread being one of the most commonly used. We therefore use the average percentage bid-ask spread (calculated relative to the mid quote) over the corresponding half-yearly period. It appears natural to presume that the higher the CDS market liquidity, the higher its contribution to credit risk discovery. As a result, a negative relationship between this illiquidity measure and the CDS market leadership is expected.

Stock turnover ratio. Turnover ratio shows how actively the stock is being traded. It is defined as the number of shares traded, adjusted by the number of shares outstanding – the turnover volume over market capitalization. This proxy for the stock market liquidity seems suitable for international sample considered in this study, as it is a unitless measure that allows direct comparison over time and geographical regions. Following the notion that the more actively the stock is being traded, the more information revelation should occur in the stock market, a positive relationship between this liquidity measure and the stock market leadership is expected. For a single half-yearly observation, the average turnover ratio over the corresponding half-yearly period is used.

Relative frequency of adverse shocks. CDS contracts, as a form of insurance, are subject to moral hazard and asymmetric information risk, especially considering that major participants in the market are primarily insiders (banks, insurance companies, hedge funds). Acharya and Johnson (2007) have shown that information revelation in the CDS market is asymmetric, consisting exclusively of bad news. Accordingly, it is expected that the information share of the CDS market will be positively related to the presence of negative and severe credit events. In line with previous study, I approximate the severity of credit deterioration by the relative frequency of adverse shocks, defined as the number days with an increase in the CDS level of more than 50 bp relative to the total number of days within the specific half-yearly period.

Credit condition. We have already seen that the lower the credit quality of the underlying reference entity, the higher the strength of the relationship between the stock and CDS markets. It seems suitable to test if the overall credit risk level also affects the relative informational dominance of considered markets. In order to achieve higher robustness in the results, I perform three alternative analyses using rating, mean CDS spread level, and a dummy variable that takes the value of 1 if the mean CDS spread level surpasses 100 bp. Credit ratings are defined numerically with values ranging from 35 for AAA issuers to 23 for BB issuers, in line with Odders-White and Ready (2006). Considered ratings correspond to those at 30 June 2003, which represents exactly the middle of the sampling period.[18]

Trend of the CDS premia. We introduce this variable as a reasonable complement for the information provided by *credit condition*. It is defined as the slope of the characteristic line over the corresponding half-yearly period. A positive sign of the slope indicates an upward trend in the CDS level and vice versa.

Time effect. The period 2002-2004 is characterized by a substantial time effect: it captures the rapid expansion of the CDS market in size and standardization, especially since 2003. We control for the substantial time effect through the introduction of two dummy variables that take the value of 1 for year 2002 and year 2004, respectively, and 0 otherwise (year 2003).[19] As the CDS market is maturing, it is expected year 2002 to have a negative effect (relative to year 2003) on the information share of the CDS market. Similarly, a positive effect for year 2004 is expected.

[18] Consequently, there is no time variation in this instance.
[19] Standard errors clustered by firm are in the level of White standard errors; therefore, I only control for the time effect through the introduction of time dummy variables.

Table 1.12 shows the correlation matrix between relevant variables.

Table 1.12 *Correlation Matrix between Relevant Variables*

Variable	% CDS bid-ask spread	Stock turnover ratio	Frequency of adverse shocks	Credit rating	Average CDS level	CDS>100
% CDS bid-ask spread	1.000					
Stock turnover ratio	-0.193	1.000				
Frequency of adverse shocks	-0.088	0.203	1.000			
Credit rating	0.426	-0.189	-0.178	1.000		
Average CDS level	-0.359	0.247	0.569	-0.486	1.000	
CDS>100	-0.312	0.213	0.355	-0.461	0.761	1.000

In the first stage of the analysis, I consider only companies for which a cointegration relationship between ICS and CDS series has been detected. Results from the analysis of half-yearly periods provide estimates of information shares for 92 firm-period observations. Although both GG and Hasbrouck's measures are commonly used in the literature (e.g. Blanco et al., 2005), the GG measure may fall out of the 0-1 range, and is completely determined by the estimated factor loadings. In contrast, Hasbrouck's measures are, by definition, always in the 0-1 range, simultaneously accounting for the variance-covariance matrix of the VECM residuals and, consequently, containing more information. Following Baillie et al. (2002), in the remainder of the study I use only the mean of the upper and lower Hasbrouck bounds (HM). Table 1.13 depicts HM information shares in terms of the stock market contribution to price discovery. These information shares are used as the dependent variable in the regression analysis.

Table 1.13 *Mid-Hasbrouck Information Shares over Half-Yearly Periods*

Company Name	Period					
	02/1	02/2	03/1	03/2	04/1	04/2
BAYER AG			0.93	0.40	0.04	0.16
ENDESA	0.78	0.82	0.30	0.82	0.46	0.89
METRO AG	0.67	0.64	0.11	0.97	0.76	0.99
STORA ENSO OYJ	0.98	0.77	0.11	0.62	0.84	0.55
TELEFONICA SA	0.92	0.51	0.16	0.25	0.40	0.14
VNU NV	0.70	0.26	0.83	0.17	0.10	0.30
BELLSOUTH CORPORATION			0.32	0.10	0.22	0.19
CATERPILLAR INC	0.99	0.84	0.63	0.14	0.95	0.95
DOW CHEMICAL CO	0.31	0.56	0.91	0.65	0.90	0.29
ELECTRONIC DATA SYSTEMS CORP			0.95	0.94	0.72	0.95
MAY DEPARTMENT STORES CO			0.99	0.82	0.75	0.44
SPRINT CORP	0.43	0.59	0.07	0.04	0.09	0.00
VISTEON CORP			0.97	0.97	1.00	0.97
FUJITSU LTD	0.96	0.96	0.87	0.99	0.99	0.59
KANSAI ELECTRIC POWER CO INC	0.56	0.02	0.06	0.04	0.59	0.44
SONY CORP	0.66	0.36	0.02	0.01	0.61	0.03
TOKYO ELECTRIC POWER CO INC	0.06	0.11	0.18	0.01	0.01	0.01
All	0.67	0.54	0.50	0.47	0.56	0.46

This table reports Mid-Hasbrouck (HM) information shares in terms of stock market contribution to price discovery over the half-yearly periods. Half-yearly information shares are estimated by imposing the entire sample cointegration equation on the half-yearly VECM.

Results from OLS regressions with White heteroskedasticity robust standard errors are summarized in Table 1.14. It seems that, despite its parsimony, the proposed econometric framework is capable of revealing significant determinants of information shares. To be precise, the set of factors considered explains approximately 30% of the variation in HM information shares. The information share of the stock market proves to be significantly influenced by the stock turnover ratio, the credit condition of the underlying reference entity, and the relative frequency of negative shocks. As expected, an increase in the stock turnover ratio implies a higher information share for the stock market. Rating, expressed numerically (i.e. a higher credit quality corresponds to a higher numerical score), seems to have a negative effect on the stock market share. This finding is corroborated with a significant positive influence of the CDS level. Finally, and consistent with the initial hypothesis, the presence of credit deterioration shocks positively influences the information share of the CDS market. The coefficients for the remaining regressors are not statistically significant.

Table 1.14 *Regression Estimation Results*

Explanatory variables	OLS estimates					
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
c	2.042 **	2.555	0.193	1.267	0.186	1.243
CDS % bid-ask spread	0.002	0.593	-0.002	-0.611	-0.002	-0.648
Stock turnover ratio	0.731 ***	3.698	0.716 ***	3.316	0.789 ***	3.665
Frequency of adverse shocks	-0.109 ***	-2.979	-0.151 ***	-4.759	-0.104 ***	-3.709
Credit condition						
Credit rating	-0.066 **	-2.297				
Average CDS level			0.001 ***	3.485		
CDS>100					0.173 *	1.965
CDS level trend	-0.006	-0.142	0.063	1.332	-0.019	-0.470
Dummy variables						
2002	0.060	0.777	0.019	0.246	0.049	0.593
2004	0.082	0.965	0.075	0.887	0.109	1.329
R^2	0.330		0.310		0.294	
adj R^2	0.273		0.251		0.234	
F-statistic	5.836		5.316		4.929	
Prob(*F*-statistic)	0.000		0.000		0.000	

This table summarizes estimates from the OLS regression, where *t*-statistics correspond to the White heteroskedasticity robust standard errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

For the sub-sample of 77 companies for which unit roots are not simultaneously detected in ICS and CDS spread series, or for which a cointegration relationship is not supported by the Johansen Cointegration Test, the analysis is replicated in an ordered probit framework. Results from Granger Causality Tests actually allow us to define a discrete dependent variable, and make the distinction between three naturally ordered, mutually exclusive states:

- ***-1** if a strict leadership of the CDS market is suggested by the Granger Causality Test (i.e. changes in CDS spreads Granger cause changes in ICSs but not the other way around);*
- ***0** if there is an unclear interpretation;*

- ***+1** if a strict leadership of the stock market is suggested by the Granger Causality Test (i.e. changes in ICSs Granger cause changes in CDS spreads, but not the other way around);*

Estimates from ordered probit regressions, performed on the basis of 388 half-yearly observations, are presented in Table 1.15. As the results show, the likelihood ratio statistics (LR) are highly significant, whereas the Pseudo-R^2 ranges from 0.056 to 0.080.[20] At first glance, some of the regression coefficients seem puzzling, when either the credit rating or a dummy variable for the mean CDS spread level above 100 bp are used as a proxy for credit condition. The CDS percentage bid-ask spread appears to be negatively related to the probability of stock market leadership, whereas credit condition exhibits weak (dummy) or null (rating) significance. It is noteworthy that a poorer credit condition and a higher CDS percentage bid-ask spread are negatively related in the sample considered in this study (see Table 1.12), a result already documented by Chen, et al. (2005). It seems, therefore, that in this instance considering either credit rating or a dummy variable as alterative proxies for credit condition generates a multicolinearity problem. The model that provides more meaningful results is the one that accounts for the credit condition by means of the average CDS level; furthermore, this is the model with the highest level of significance (LR statistic of 45.408 and Pseudo-R^2 of 0.080). Again, the presence of a severe deterioration in the credit quality of the underlying issuer negatively influences the probability of the stock market leadership. Still, a higher overall creditworthiness positively affects this probability. Different variables actually confirm this finding, as not only the mean CDS spread level shows a positive relationship to the probability of stock market leadership, but the CDS trend also points in the same direction. In contrast, neither the CDS percentage bid-ask spread nor the

[20] These values may appear low; however, I am dealing with discrete models in which this measure is of secondary importance. The primary interest lies in the statistical and economic significance of the regression coefficients.

stock turnover ratio seem to have any significant influence on the information shares. It turns out that the probability of the stock market leadership is highly associated with the year 2002, in line with the initial hypothesis.

Table 1.15 *Ordered Probit Estimation Results for the Sub-Sample of 77 Companies*

Explanatory variables	Ordered probit estimates					
	coef	*z*-stat	coef	*z*-stat	coef	*z*-stat
% CDS bid-ask spread	-0.017 ***	-3.017	-0.007	-1.221	-0.013 **	-2.496
Stock turnover ratio	0.353	1.528	0.273	1.177	0.312	1.357
Frequency of adverse shocks	-0.389 **	-1.973	-1.033 ***	-4.018	-0.525 **	-2.507
Credit condition						
Credit rating	-0.007	-0.211				
Average CDS level			0.006 ***	3.940		
CDS>100					0.346 *	1.830
CDS level trend	0.192	1.101	0.507 ***	2.645	0.277	1.548
Dummy variables						
2002	0.547 ***	3.035	0.474 ***	2.626	0.487 ***	2.709
2004	-0.092	-0.615	-0.058	-0.387	-0.105	-0.705
Log likelihood	-264.889		-260.292		-266.574	
Pseudo R^2	0.056		0.080		0.058	
LR stat - χ^2_7	31.212		45.408		32.844	
Prob(*LR* stat)	0.000		0.000		0.000	

This table reports the ordered probit estimation results for the sub-sample of 77 companies that either do not have unit roots, or for which a cointegration relationship is not distinctly suggested by the Johansen Cointegration Test. The dependent variable takes the value of -1 for the clear CDS market leadership, the value of 0 for the situation in which no clear interpretation can be made, and the value of +1 for the clear stock market leadership in credit risk discovery. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

In order to enhance previous analysis, I apply the ordered probit framework to the entire sample containing 480 half-yearly observations. Specifically, I merge two approaches that, on a complementary basis, indicate the relative informational dominance of the stock and CDS markets and, at the bottom, lead to three possible, mutually exclusive situations: a) clear stock market leadership in credit risk discovery, b) clear CDS market leadership, and c) a situation in which no obvious interpretation can be made. Consequently, I introduce three dummy variables that take the value of:

- ***-1*** *if either the VECM or the Granger Causality Test, whichever is appropriate, suggests a strict leadership of the CDS market. In the case of ICS and CDS spread series being cointegrated, this value will be associated with the situation in which loading factor λ_1 is significantly negative, while λ_2 has no statistical significance (i.e. only ICSs adjust to eliminate pricing errors); and, in the case of ICS and CDS spread series not being cointegrated, this value will be associated with the situation in which changes in CDS spreads Granger cause changes in ICSs, but not the other way around;*
- ***0*** *if there is unclear interpretation;*
- ***+1*** *if either the VECM or the Granger Causality Test, whichever is appropriate, suggests a strict leadership of the stock market. In the case of ICS and CDS spread series being cointegrated, this value will be associated with the situation in which loading factor λ_2 is significantly positive, while λ_1 has no statistical significance (i.e. only CDS spreads adjust to eliminate pricing errors); and, in the case of ICS and CDS spread series not being cointegrated, this value will be associated with the situation in which changes in ICSs Granger cause changes in CDS spreads, but not the other way around;*

Ordered probit estimation results for the complete sample are reported in Table 1.16. Again, the model using the average CDS level as a proxy for credit condition provides the more meaningful results and the highest significance level. In line with previous findings, estimated coefficients for stock turnover ratio, relative frequency of adverse shocks, average CDS spread level, CDS trend, and dummy variable for the year 2002, are found to be statistically significant with the expected signs.

Table 1.16 *Ordered Probit Estimation Results*

Explanatory variables	Ordered probit estimates					
	coef	*z*-stat	coef	*z*-stat	coef	*z*-stat
CDS % bid-ask spread	-0.012 **	-2.361	-0.006	-1.194	-0.011 **	-2.261
Stock turnover ratio	0.478 **	2.234	0.428 **	1.992	0.470 **	2.207
Frequency of adverse shocks	-0.249 **	-2.224	-0.643 ***	-4.354	-0.320 ***	-2.729
Credit condition						
Credit rating	-0.030	-1.034				
Average CDS level			0.005 ***	4.339		
CDS>100					0.365 **	2.294
CDS level trend	0.223 *	1.777	0.516 ***	3.472	0.270 **	2.118
Dummy variables						
2002	0.429 ***	2.798	0.334 **	2.167	0.376 **	2.460
2004	-0.039	-0.299	0.002	0.013	-0.015	-0.112
Log likelihood	-367.399		-358.172		-365.285	
Pseudo R^2	0.045		0.069		0.051	
LR stat - χ^2_7	34.773		53.227		39.001	
Prob(*LR* stat)	0.000		0.000		0.000	

This table presents ordered probit estimation results, where the dependent variable takes the value of -1 in case of clear CDS market leadership, the value of 0 for the situation in which no obvious interpretation can be made, and the value of +1 in case of clear stock market leadership. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

In order to ensure the robustness of the results, I perform a probit analysis directly confronting two extreme cases. More specifically, I introduce a dummy variable that takes only two values: 1 in the case of strict stock market leadership and 0 in case of strict CDS market leadership. Results of such probit analysis with a sub-sample of 151 half-yearly observations are reported in Table 1.17. Apart from a higher Pseudo-R^2 (0.188 for the model that includes the average CDS level), results are completely consistent with previous findings.

Table 1.17 *Probit Estimation Results*

Explanatory variables	Probit estimates					
	coef	*z*-stat	coef	*z*-stat	coef	*z*-stat
c	1.657	0.891	-0.059	-0.115	0.345	0.767
CDS % bid-ask spread	-0.019	-1.510	-0.011	-1.032	-0.017	-1.549
Stock turnover ratio	1.869 ***	2.794	1.611 **	2.176	1.706 ***	2.604
Frequency of adverse shocks	-0.519 *	-1.894	-1.050 **	-2.498	-0.626 **	-2.211
Credit condition						
Credit rating	-0.047	-0.684				
Average CDS level			0.006 **	2.206		
CDS>100					0.346	1.102
CDS level trend	0.622 **	2.123	0.971 **	2.219	0.696 **	2.328
Dummy variables						
2002	0.689 **	2.158	0.646 *	1.894	0.662 **	2.133
2004	0.040	0.136	0.045	0.154	0.011	0.037
Log likelihood	-71.820		-70.724		-73.041	
Pseudo R^2	0.167		0.188		0.162	
LR stat - χ^2_7	28.877		32.840		28.208	
Prob(*LR* stat)	0.000		0.000		0.000	

This table presents probit estimation results, where the dependent variable takes the value of 1 in the case of clear stock market leadership and the value of 0 in the case of clear CDS market leadership. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

1.6 Conclusions

The credit risk of any given company is implicitly or explicitly reflected through market prices of different credit sensitive claims, including stocks and credit default swaps. Markets where these assets are traded differ in several dimensions – organization, liquidity, participants – leading to probable differences in the speed of incorporation of new information. In this context, the key question becomes to determine the relative informational dominance of respective markets. Although this issue has been the focus of recent studies, the analyses conducted in this chapter goes beyond the existing literature by investigating the driving forces behind the credit risk discovery process. Specifically, I analyze factors underlying the dynamic relationship between stock market implied credit spreads and CDS spreads in a time-varying context. The analysis is based on a large international sample of 94 US, European, and Japanese companies, tracked over the 2002-2004 period.

In this chapter I provide empirical evidence that allows for several conclusions. First, credit risk discovery in the stock and CDS markets is a dynamic process. Although the obtained results do not contradict the leading role of the stock market documented in previous studies, I do find a downward trend in this pattern over the period considered. Second, the relative informational dominance of the stock market is significantly influenced by the overall credit condition of the reference entity. The probability of the stock market leading credit risk discovery increases with the level of credit risk, as does the strength of the relationship between the two markets. Yet, consistent with the argument of insider trading in the market for credit derivatives, the probability of the CDS market leading credit risk discovery is positively related to the presence of severe credit deterioration shocks.

Chapter 2

Pseudo Maximum Likelihood Estimation of Structural Credit Risk Models with Exogenous Default Barrier

2.1 Introduction

Thirty-five years after Merton's (1974) seminal paper, no consensus yet exists on the ability of structural models to reflect the credit risk of companies.[21] Under the structural setting, debt and equity are treated as contingent claims on the underlying firm's asset value, which, accordingly, becomes the fundamental source of uncertainty driving credit risk. Following this argument, structural models should be able to transform the information on a firm's asset value process provided by equity prices into the information on credit risk provided, in turn, by credit spreads. This ability of structural models to explain observable market levels of credit spreads has been precisely the cornerstone of most empirical tests. Until recently, the broadly accepted conclusion was that in this regard structural models have not been very successful (Jones et al., 1984; Ogden, 1987; Lyden and Saraniti, 2001; Huang and Huang, 2003; Eom et al., 2004).

The theoretical completeness of structural models has raised a question, however: To what extent could this seemingly poor performance actually be a product of the estimation methods applied? Key determinants of credit spreads – a firm's asset value and volatility, along with the default barrier – represent pure latent variables; thus, any empirical test necessarily represents a simultaneous test of both the structural model at hand and the

[21] Merton's (1974) model was subsequently extended by Black and Cox (1976), Geske (1977), Longstaff and Schwartz (1995), Leland (1994), Leland and Toft (1996), Collin-Dufresne and Goldstein (2001), Zhou (2001), and others.

estimation method itself. Ericsson and Reneby (2005) and Li and Wong (2008) have shown that the empirical performance of structural models is, in fact, largely undermined by traditional approaches to the estimation of the firm asset value and volatility (i.e. proxy and volatility restriction methods). On the contrary, the maximum likelihood (ML) approach – novel in this context and first motivated by Duan (1994, 2000) – provides much greater support for theoretically appealing structural credit risk models.[22]

In a similar vein, increasing attention is being paid to the exact definition of the default barrier. In general, the default triggering firm asset value may either be set exogenously (e.g. Longstaff and Schwartz, 1995) or endogenously obtained inside the model as the optimal decision for equity holders (e.g. Nielsen et al., 1993; Leland, 1994; Leland and Toft, 1996).[23] Although this second alternative seems more appealing, it ignores the potential influence of other factors on the event of default (e.g. debt covenants, liquidity restrictions, insolvency codes). A more recent approach is based on the assumption of an exogenous default barrier; but rather than imposing a somewhat arbitrary value (e.g. the debt's face value, KMV's default point), market data are used to derive this model parameter. Wong and Choi (2009) consider this possibility in the case of the down-and-out call valuation model discussed by Brockman and Turtle (2003). Specifically, they maximize the likelihood function for the time series of equity prices not only as a function of the expected rate of return and volatility of the firm assets, but also as a function of the default barrier. Wong and Choi's paper provides an insightful analysis of some of the drawbacks of using the proxy approach – as in Brockman and Turtle (2003); however, their results also indicate that

[22] Traditional approaches dominate the literature (Jones et al., 1984; Ronn and Verma, 1986; Ogden, 1987; Anderson and Sundaresan, 2000; Lyden and Saraniti, 2001; Brockman and Turtle, 2003; Delianedis and Geske, 2003; Eom et al., 2004). The maximum likelihood approach (Ericsson and Reneby, 2005; Ericsson et al., 2007; Li and Wong; 2008, Wong and Choi, 2009) is not the unique option, however. Other approaches include simulated maximum likelihood (Bruche, 2004, 2007; Duan and Fulop, 2009) and iterative schemes (Vassalou and Xing, 2004; Forte, 2009).

[23] In Merton's (1974) model, default can occur only at maturity of the debt. Following the ideas of Black and Cox (1976), this assumption was subsequently surpassed by allowing a firm to default at any time if the market value of its assets falls below some critical lower threshold value – the default barrier.

standard maximization of the likelihood function can generate misleading results. To be precise, at least 25% of their reported barriers are equal to zero, whereas almost 45% are above nominal debt and 25% of those values are above two-and-a-half times the face value of the debt.[24]

Misleading results from likelihood maximization are typically a reflection of an ill-behaved likelihood function – an old problem in statistics that more commonly appears with an increase in the number of unknown parameters – as in the present case. Under these circumstances, however, *ad hoc* procedures can sometimes be defined which, following the spirit of likelihood maximization, are naturally referred to as pseudo maximum likelihood estimation methods (e.g. Gong and Samaniego, 1981). In this chapter one such method for the estimation of structural credit risk models with exogenous default barrier is proposed. More explicitly, an iterative algorithm is defined, which, based on the log-likelihood function for the time series of equity prices, provides pseudo ML estimates of the default barrier and of the value, volatility, and expected rate of return on the firm's assets. The suggested approach is tested empirically using an international sample of 96 companies, whereas the reference credit risk model corresponds to the modified version of Leland and Toft's (1996) model suggested by Forte (2009). It is shown that – in line with Wong and Choi (2009) – the standard ML approach results in unreal barriers for a substantial proportion of the companies considered. On the contrary, the pseudo ML approach suggested in this chapter generates reasonable values that fall in the range of 50.3% to 96.9% of the principal value of debt. In terms of credit default swap (CDS) spread estimation, theoretical credit spreads based on the proposed method provide the lowest pricing errors when compared to other options that are

[24] Wong and Choi's results are not tested in light of their accuracy for credit spread estimation; it is very intuitive, however, that credit spreads will be equal to zero for zero default barriers. Furthermore, in the case of default boundaries in the order of two-and-a-half times (or more) the face value of the debt, reasonable credit spread estimates could be derived only at the cost of assuming unreasonably large bankruptcy costs.

usually considered when specifying the default barrier: standard ML estimate, endogenous value, KMV's default point, and principal value of debt.[25]

It is worth noting that recent studies suggest using CDS data in addition to equity data for the estimation of structural credit risk models. Predescu (2005), for example, derives the joint likelihood function for the time series of equity prices and CDS spreads, where the equity pricing equation corresponds to the same down-and-out call valuation model analyzed by Brockman and Turtle (2003) and Wong and Choi (2009). Additional information on CDS premia guarantees a well-behaved likelihood function and, consequently, standard likelihood maximization provides default barrier estimates within reasonable bounds in this case.[26] Following a different approach, Forte (2009) employs an iterative scheme to derive the time series of firm asset values and the corresponding volatility from the time series of equity prices, whereas the default barrier is calibrated from the time series of CDS spreads. Again, use of both equity and CDS data ensure reasonable results for most of the cases.

In this chapter I explicitly refrain from using market data other than equity prices. Although the use of CDS spreads for the estimation of structural models undoubtedly represents an appealing approach, it does not allow for the most common situation in which such information is either unavailable or unreliable. As this is exactly the situation in which information regarding credit risk becomes more valuable, this is the one that is presumed in this chapter.

The remainder of the chapter is structured as follows. Section 2.2 describes the structural model setting. Section 2.3 summarizes the standard ML approach. Section 2.4

[25] The use of CDS spreads as a reference is motivated by a second, not minor, problem in previous empirical tests: the traditional use of corporate-government yield spreads as a benchmark clashes with the evidence on non-credit risk factors in bond premia (Collin-Dufresne, et al., 2001). Accordingly, CDS spreads are increasingly seen as a preferred choice, further providing stronger support for structural credit risk models (Ericsson et al., 2007; Ericsson et al., 2009; Forte, 2009).

[26] Predescu also analyzes the case in which only equity data are employed for the estimation. She concludes that "using only equity prices, the estimation cannot pinpoint the optimal value for the default point for most of the firms" (Predescu, 2005; p. 19).

presents the proposed alternative: the pseudo ML estimation approach. Other methods that are usually applied in determining the default barrier are briefly discussed in Section 2.5. Section 2.6 offers a full description of the data set. Section 2.7 provides the empirical results, in terms of both parameter estimates and predicted spreads. The main conclusions are drawn in Section 2.8.

2.2 The Structural Model Setting

As a reference credit risk model, I consider the modified version of Leland and Toft's (1996) model suggested by Forte (2009). This model has already been shown to generate reasonable predictions on credit spreads as long as the appropriate default barrier is selected; therefore, it seems suitable for testing the performance of the pseudo ML estimation approach that is proposed in this chapter. Here I merely describe the main features of the model, referring the interested reader to the original paper for details.

The market value of total assets at any time t, V_t, is assumed to evolve according to the continuous diffusion process:

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dz_t, \tag{2.1}$$

where μ is the expected rate of return on the asset value, δ is the fraction of the asset value paid out to investors, σ is the asset return volatility, and z is a standard Brownian motion. Default occurs whenever V_t reaches a specific critical point V_b, defined as a fraction β of the nominal value of total debt P:

$$V_b = \beta P. \tag{2.2}$$

The value of an individual bond d_n, with maturity τ_n, principal p_n, and constant coupon flow c_n, is given by:

$$d_n(V_t, \tau_n) = \frac{c_n}{r} + e^{-r\tau_n}\left[p_n - \frac{c_n}{r}\right][1 - F_t(\tau_n)] + \left[(1-\alpha)\beta p_n - \frac{c_n}{r}\right]G_t(\tau_n), \tag{2.3}$$

for $n = \{1, \dots, N\}$, where r is the risk-free rate, α represents bankruptcy costs, and expressions for $F_t(\tau_n)$ and $G_t(\tau_n)$ are given in Appendix A. The total debt value is then represented by the sum of all outstanding bonds:

$$D(V_t) = \sum_{n=1}^{N} d_n(V_t, \tau_n). \tag{2.4}$$

Finally, the equity value is expressed as:

$$S_t = g(V_t) = V_t - D(V_t | \alpha = 0), \tag{2.5}$$

where $D(V_t|\alpha = 0)$ is the market value of total debt when bankruptcy costs equal zero. This expression follows from the reasoning that the presence of bankruptcy costs affects only creditors who, in case of default, receive only a fraction $(1-\alpha)$ of the firm's asset value.

2.3 Standard Maximum Likelihood Estimation

In order to overcome the problem of unobservability of the asset value process and the default barrier parameter β, it is possible to apply ML estimation using the transformation of variables technique – an idea originally introduced by Duan (1994, 2000). When applied to this specific problem, the observable data set of equity values $S = \{S_t;\ t = 1, \dots, T\}$, can be treated as a transformed data set of the unobservable underlying firm asset values $V = \{V_t;\ t = 1, \dots, T\}$. The ML procedure is then carried out by deriving the log-likelihood function for the transformed equity values $L_s(S; \theta)$, where the theoretical equity pricing formula of the structural model at hand, $S_t = g(V_t; \theta)$; $t = \{1, \dots, T\}$, serves as a strictly monotonic, one-to-one transformation function. Accordingly, θ represents the set of unknown parameters to be estimated, along with the complete vector of unobservable firm asset values V.

Regardless of the specificities of the underlying structural model, a complete closed-form solution for the log-likelihood function of the observable data set S, could be derived using standard results on differentiable transformations. Accounting for the survivorship issue under the first-passage time framework, and in the simplest case of exogenous and constant default barrier, such log-likelihood function can be expressed as (Duan et al., 2003, 2004):[27]

$$\begin{aligned} L_s(S;\theta) &= L\big(\hat{V};\sigma,\mu,\beta\big) \\ &= L_v\big(\hat{V};\sigma,\mu\big) + \sum_{t=2}^{T} \ln\left[1 - e^{\left(\frac{-2}{\sigma^2\Delta t}\right) ln\left(\frac{\hat{V}_{t-1}}{V_b}\right) ln\left(\frac{\hat{V}_t}{V_b}\right)}\right] \\ &- \ln[P_{nd}(\sigma,\mu,\beta)] - \sum_{t=2}^{T} \ln\left|\frac{\partial g\big(\hat{V}_t;\sigma,\beta\big)}{\partial \hat{V}_t}\right|, \end{aligned} \tag{2.6}$$

where $\hat{V}$ represents the vector of implied firm asset values for a given set $\{\sigma,\beta\}$, and for the invertible equity pricing equation $\hat{V}_t = g^{-1}(S_t;\sigma,\beta)$.

The first term in expression (2.6) reflects the log-likelihood function for the time series of the log-normally distributed firm asset values:

$$\begin{aligned} L_v\big(\hat{V};\sigma_v,\mu\big) &= -\sum_{t=2}^{T} \ln \hat{V}_t - \frac{T-1}{2} ln(2\pi\sigma^2\Delta t) \\ &- \frac{1}{2\sigma^2\Delta t}\sum_{t=2}^{T}\left[\ln\left(\frac{\hat{V}_t}{\hat{V}_{t-1}}\right) - \left(\mu - \delta - \frac{\sigma^2}{2}\right)\Delta t\right]^2. \end{aligned} \tag{2.7}$$

[27] Maximum likelihood estimation in this context is applicable only in the case where the default barrier is defined as a constant, or a certain time-dependent deterministic function.

The next two terms account for the survivorship issue, with $P_{nd}(\theta)$ actually denoting the survival probability during the entire sample period:

$$P_{nd}(\sigma,\mu,\beta) = \boldsymbol{\Phi}\left[\frac{\left(\mu-\delta-\frac{1}{2}\sigma^2\right)(T-1)\Delta t - ln\left(\frac{V_b}{\hat{V}_1}\right)}{\sigma\sqrt{(T-1)\Delta t}}\right] - e^{\left(\frac{2}{\sigma^2}\right)\left(\mu-\delta-\frac{\sigma^2}{2}\right)ln\left(\frac{V_b}{\hat{V}_1}\right)}\boldsymbol{\Phi}\left[\frac{\left(\mu-\delta-\frac{1}{2}\sigma^2\right)(T-1)\Delta t + ln\left(\frac{V_b}{\hat{V}_1}\right)}{\sigma\sqrt{(T-1)\Delta t}}\right], \tag{2.8}$$

where $\boldsymbol{\Phi}(\cdot)$ refers to the standard normal distribution function.

The fourth and final term in expression (2.6) reflects the Jacobian of the transformation. Appendix B provides the exact analytical expression for the derivative of the transformation, $g(V_t;\sigma,\beta)$,in the particular case of the model proposed by Forte (2009).

Following the conventional principle of likelihood maximization, the standard approach derives the entire set of unobservable parameters by solving the maximization problem:

$$Max_{\{\sigma,\mu,\beta\}} \quad L(\hat{V};\sigma,\mu,\beta). \tag{2.9}$$

2.4 Pseudo Maximum Likelihood Estimation

In most empirical applications, the exogenous default barrier is predefined, either at the face value of the debt, or at a given fraction of this value (e.g. KMV's default point). In such cases, the likelihood function is well-behaved in the parameter space $\theta = \{\sigma,\mu\}$, and numerical maximization is always feasible. The complexity of the problem, however, is further augmented when the default barrier itself belongs to the parameter space, $\theta = \{\sigma,\mu,\beta\}$. In this case, the likelihood function sometimes exhibits a nonstandard behavior when applied to real data, and numerical routines may converge to spurious parameter values, particularly for the default barrier.

As an alternative to the standard ML approach described in the previous section, a pseudo ML estimation method is suggested in this chapter. Note first that the unrestricted maximization problem in the parameter space $\{\sigma, \mu, \beta\}$ described in (2.9) could be actually thought of as a restricted maximization problem in the space $\{V, \sigma, \mu, \beta\}$, specifically,

$$Max_{\{V,\sigma,\mu,\beta\}} \quad L(V, \mu, \sigma, \beta) \quad s.t. \;\; \{V_t = g^{-1}(S_t; \sigma, \beta);\; t = 1, \dots, T\}, \tag{2.10}$$

where the restriction $V_t = g^{-1}(S_t; \sigma, \beta)$ states that for any possible set of parameter values $\{\sigma, \beta\}$, the firm asset value at t is derived by inverting the transformation function. Referring specifically to the problem that default barrier estimates could often reach unreasonable values under the standard maximization approach, I propose an estimation of the set of unknown parameters $\theta = \{\sigma, \mu, \beta\}$, along with the whole vector of a firm's asset values V, by means of the following iterative algorithm:

Step 1. Propose an initial value for the default-to-debt ratio β_0, and estimate the time series of the firm's asset values V, the volatility σ, and the expected rate of return μ, by solving the restricted maximization problem:

$$Max_{\{V,\mu,\sigma\}} \quad L(V, \sigma, \mu | \beta_0) \quad s.t. \;\; \{V_t = g^{-1}(S_t; \sigma, \beta_0);\; t = 1, \dots, T\}. \tag{2.11}$$

In this way a set of ML estimates V_0, σ_0 and μ_0 is derived conditional on the predefined value of β, β_0.

Step 2. Departing from the obtained set of ML estimates in Step 1, solve the unrestricted maximization problem:

$$Max_{\{\beta\}} \quad L(\beta | V_0, \sigma_0, \mu_0); \tag{2.12}$$

This will generate a pseudo ML estimate of β, β_1, given the predefined values V_0 , σ_0 and μ_0.

Step 3. If $\beta_1 = \beta_0$, convergence is attained. If not, set $\beta_0 = \beta_1$ in Step 1 and repeat until convergence is achieved.

This algorithm provides estimates of parameter values σ, μ, and β, and of the whole vector of the firm's asset values V that do not necessarily maximize the log-likelihood function globally, as in the standard procedure. It does, however, offer several noteworthy properties. (a) Estimates of σ, μ, and the whole vector of the firm's asset values V are estimates obtained at the global maximum point of the log-likelihood function, conditional upon the default barrier level (Step 1). (b) The default barrier is not arbitrarily fixed, but is determined conditional on the other parameter values and on the whole set of the firm's asset values (Step 2). (c) The final solution of the algorithm guarantees that the equity pricing equation is satisfied for all t, providing a consistent overall set of final parameter estimates (Steps 1 and 3). (d) Empirical results confirm that this final outcome is, in fact, unique, independent of the initial value of β, β_0. (e) The proposed procedure offers the major advantage of generating much more meaningful default barrier estimates than the standard ML approach does. This property is further discussed in Section 2.7.

2.5 Other Default Barrier Specifications

For completeness, it seems suitable to include in the analysis other approaches that are usually considered in determining the default barrier. In particular, I account for the endogenous value, KMV's default point, and nominal debt value.

- ***Endogenous value:*** Endogenous default models assume the default point to be optimally chosen by equity holders. It is specifically derived by invoking the smooth-pasting condition (e.g. Leland and Toft, 1996):

$$\left.\frac{\partial g(V_t)}{\partial V_t}\right|_{V_t=V_b} = 0. \tag{2.13}$$

In the case of the model suggested by Forte (2009), the endogenous default-to-debt ratio is given by:

$$\beta_{END} = \frac{\sum_{n=1}^{N}\left\{e^{-r\tau_n}\left[p_n - \frac{c_n}{r}\right]A(\tau_n) + \frac{c_n}{r}B(\tau_n)\right\}}{P + \sum_{n=1}^{N} p_n\, B(\tau_n)}, \tag{2.14}$$

where exact expressions for $A(\tau_n)$ and $B(\tau_n)$ are given in Appendix C.[28]

- ***KMV's default point:*** In the KMV methodology, the default point is determined as short-term liabilities plus 50% of long-term liabilities. In terms of the default-to-debt ratio,

$$\beta_{KMV} = \frac{STL + 0.5 \times LTL}{P}. \tag{2.15}$$

- ***Nominal debt value:*** Under the simplest assumption, the default barrier is set at the face value of the debt:

$$\beta_P = 1. \tag{2.16}$$

It is also worth noting that under these default barrier specifications, estimates of the firm's asset value and volatility must still be defined. In further empirical tests, and for the aim of rational comparisons, the ML approach will be used in these cases. More formally, the restricted maximization problem

$$Max_{\{V,\sigma,\mu\}} \quad L(V,\mu,\sigma|\beta_j) \quad s.t. \ \{V_t = g^{-1}(S_t;\sigma,\beta_j);\ t = 1,\dots,T\}, \tag{2.17}$$

for $j = \{END, KMV, P\}$ will be solved.

[28] See also Alonso et al. (2008).

2.6 Data

The data set corresponds to the final sample of 96 nonfinancial companies (41 European, 32 US, and 23 Japanese) analyzed by Alonso et al., (2008). This data set comprises the entire period 2002-2004, containing:

- Daily data on market capitalization (close of business) obtained from DataStream.
- Daily data on 1- to 10-year locally denominated swap rates, also gathered from DataStream.
- Accounting items referring to short- and long-term liabilities, interest expenses, and cash dividends, collected from WorldScope.
- Daily data on CDS spreads (mid bid-ask quotes) obtained, at the close of business in London, New York and Tokyo, from CreditTrade. These data include only 5-year contracts denominated in local currency (euro, dollar, or yen). Furthermore, each company contains CDS data for at least two consecutive years, with a minimum of 150 observations per year.[29]

Using these data, those model inputs that are treated as known or observable, whether the standard or pseudo ML estimation method is employed, are defined. Namely,

a) Equity value: Daily data on equity value, $S_t;\ t = 1, \dots, T$, will correspond to daily data on market capitalization.

b) Debt's principal value P: Given that P is treated as a constant, I use the sum of the average short-term liabilities (STL) and long-term liabilities (LTL).

c) Debt structure: In line with expression (4), the debt structure needs to be defined – the number of individual bonds (N) and their corresponding characteristics: time to maturity

[29] In their final sample, Alonso et al. (2008) include the year 2001 as well. In this study, I exclude that year, however, as CDS series satisfying the inclusion criteria were available for only eight companies.

(τ_n), coupon (c_n), and principal (p_n). In order to resemble the true debt structure as much as possible, I adopt Forte's (2009) approach, and assume that at each instant t the company has ten bonds – one with a maturity of one year and principal equal to STL and nine with maturity ranging from two to ten years, each with principal equal to 1/9 of LTL. The coupon of each bond is determined as the fraction of average interest expenses (IE) proportional to the weight of the principal of each individual bond p_n, over the total principal value of debt P.

d) Payout rate: The payout rate δ is determined as the average annualized payment of interest expense (IE) and cash dividends (CD) to the proxy value of the firm, calculated as the sum of market value of equity and book value of total liabilities.

e) Risk-free interest rate: The risk-free rate for each individual bond is determined according to the swap rate for the corresponding maturity.

f) Recovery rate: Once the estimation of the unknown parameter values and firm asset values has been completed, theoretical stock market implied credit spreads (ICS) can be derived as the spread from issuing, at par value, a hypothetical bond with the same maturity as the CDS spread that serves as a benchmark (five years in this case).[30] In principle, this requires to define a value for the bankruptcy costs α, which enters in expression (3) through the recovery rate, $(1-\alpha)\beta$. In terms of CDS spread valuation, however, the market practice is to consider a fixed recovery rate of 40%. For the aim of simplicity and more robust comparisons, I also adopt this convention.

Main descriptive statistics for the sample considered are depicted in Table 2.1. The average company in the sample has market capitalization of approximately $26.7 billion. Equity volatility, defined as the unconditional annualized standard deviation of the

[30] See Forte (2009) for details.

continuously compounded returns on equity, ranges around 36.9%. The mean leverage, calculated as the book value of total liabilities over the sum of market capitalization and book value of total liabilities, amounts to 52.7%. Yet the leverage of the companies in the sample varies, with indebtedness ranging from 3.8% to 92.1%. Regarding CDS spreads, the mean level for the entire period considered ranges from 11.33 bp to 306.40 bp on an individual firm basis, with the overall cross-sectional mean for all entities being 71.82 bp. The average number of daily observations per company is 630, whereas the majority of the companies in the sample refer to A and BBB rated issuers.

Table 2.1 *Descriptive statistics*

Statistics	MC (mm $)	Equity Volatility	Leverage	CDS (bp)	Bid-Ask Spread (bp)	No. of daily observations per company	Rating (No. of companies)	
Mean	26,705.41	0.37	0.53	71.82	13.29	630	AAA-AA	(14)
Median	14,431.07	0.36	0.53	53.37	10.40	712	A	(41)
SD	37,858.73	0.09	0.20	62.24	10.31	129	BBB	(35)
Min	1,082.89	0.16	0.04	11.33	4.72	418	BB	(4)
Max	310,471.20	0.69	0.92	306.40	73.62	759	ND	(2)

This table reports the main descriptive statistics on a cross-sectional basis. The overall sample includes 96 nonfinancial companies. MC refers to market capitalization in millions of dollars. 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 over the sum of market value of equity and book value of total liabilities. CDS spreads refer to the mid bid-ask quote.

2.7. Results

2.7.1. Parameter values

Final results on parameter values are shown in Table 2.2, including estimates provided by the standard ML approach (MLE), estimates from the pseudo ML approach (ALG), and estimates resulting from the assumption of an endogenous default barrier

(END).[31] Main descriptive statistics in Panel A indicate that standard maximization of the log-likelihood function leads to default barriers which are, on average, higher than the face value of the debt (mean β_{MLE} of 1.093). In addition, the dispersion is significant, with a minimum of 0.025 and a maximum of 6.762. These types of results are difficult to reconcile with economic intuition. In the first case, the probability of default is almost nil; in the second situation, the firm is not able to continue running operations, even when the firm asset value is worth as much as 6.7 times the face value of the debt. Moreover, predicted credit spreads will be unreasonable in both cases.[32]

Table 2.2 *Parameter estimates*

Panel A. Descriptive Statistics

	Mean	Median	SD	Min	Max
Standard ML Estimation					
β_{MLE}	1.093	0.909	0.823	0.025	6.762
σ_{MLE}	0.145	0.132	0.089	0.039	0.542
μ_{MLE}	0.021	0.026	0.060	-0.163	0.178
Pseudo ML Estimation					
β_{ALG}	0.801	0.804	0.085	0.503	0.969
σ_{ALG}	0.164	0.154	0.091	0.041	0.542
μ_{ALG}	0.027	0.027	0.067	-0.164	0.239
Endogenous Default Barrier					
β_{END}	0.752	0.762	0.097	0.438	0.945
σ_{END}	0.164	0.154	0.091	0.039	0.541
μ_{END}	0.027	0.027	0.067	-0.162	0.239

Panel B. Distribution of Default-to-Debt Ratios

Range	β_{MLE}	β_{ALG}	β_{END}
[0.0 - 0.1]	4	0	0
(0.1 - 0.2]	3	0	0
(0.2 - 0.3]	1	0	0
(0.3 - 0.4]	0	0	0
(0.4 - 0.5]	0	0	2
(0.5 - 0.6]	3	3	7
(0.6 - 0.7]	3	7	14
(0.7 - 0.8]	15	36	44
(0.8 - 0.9]	19	39	24
(0.9 - 1.0]	16	11	5
(1.0 - 1.1]	3	0	0
(1.1 - 1.2]	6	0	0
> 1.2	23	0	0

This table reports the main descriptive statistics of the parameter estimates (Panel A), along with the distribution of default-to-debt ratios (Panel B). Results from the standard ML approach, the pseudo ML approach, and the endogenous default barrier approach are considered.

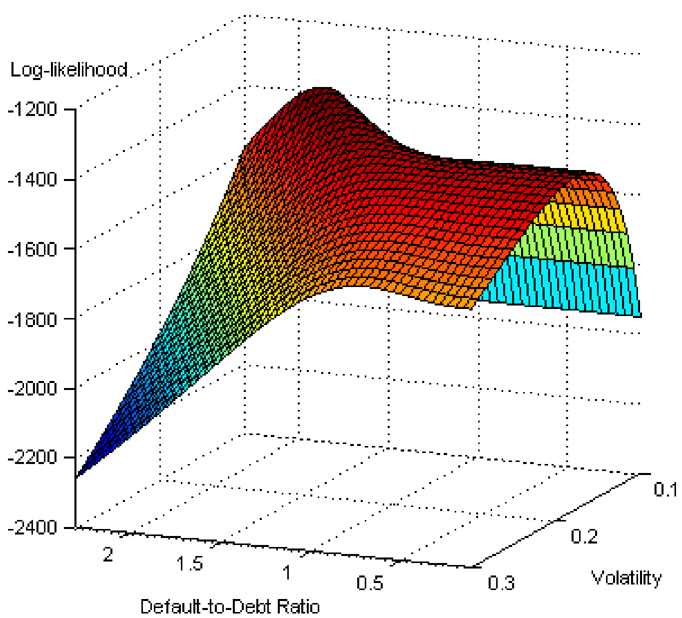
[31] The convergence criterion for the pseudo ML estimation algorithm is set at $1\text{x}10^{-6}$

[32] Take, for instance, the upper bound, 6.7. In case of default, and assuming bankruptcy costs of around 30% (Leland, 2004), debt holders receive 4.7 times the face value of the debt. Under these circumstances, the credit spread will actually be negative.

These puzzling results are an indication of a likelihood function that is not well-behaved. Figure 2.1, for example, presents the behavior of the log-likelihood function for BASF AG. It is apparent that a global maximum is not achieved in this case for any reasonable default-to-debt ratio, and standard log-likelihood maximization actually converges to a misleading value of 2.085. A whole distribution of default-to-debt ratios in Table 2.2, Panel B, suggests that a similar situation is, in fact, repeated for a significant number of companies. Notwithstanding, reasonable values are also achieved for many of the cases. Take, for instance, the log-likelihood function of Bouygues SA shown in Figure 2.2. Even though this log-likelihood function is relatively flat in terms of the default-to-debt ratio, the obtained value from the standard approach (0.783) represents a reasonable estimate. In summary, it can be concluded that the standard ML approach neither rules out nor guaranties reasonable results.

Figure 2.1 *Behavior of the Log-Likelihood Function for BASF AG*

Company: BASF AG



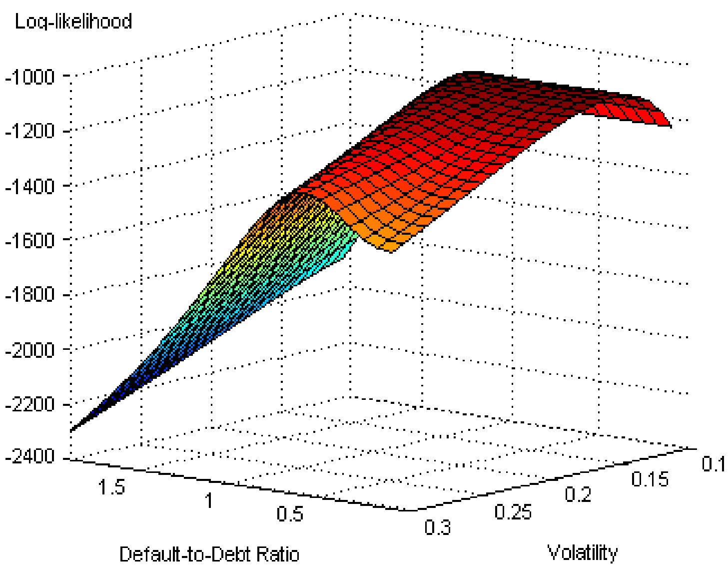
Standard ML Estimation	
β_{MLE}	2.085
σ_{MLE}	0.079
μ_{MLE}	0.037

Pseudo ML Estimation	
β_{ALG}	0.778
σ_{ALG}	0.176
μ_{ALG}	0.047

Endogenous Default Barrier	
β_{END}	0.702
σ_{END}	0.176
μ_{END}	0.047

Figure 2.2. *Behavior of the Log-Likelihood Function for Bouygues SA*

Company: Bouygues SA



Standard ML Estimation	
β_{MLE}	0.783
σ_{MLE}	0.138
μ_{MLE}	-0.006

Pseudo ML Estimation	
β_{ALG}	0.789
σ_{ALG}	0.138
μ_{ALG}	-0.006

Endogenous Default Barrier	
β_{END}	0.779
σ_{END}	0.138
μ_{END}	-0.006

On the opposite side, parameter estimates from both the pseudo ML approach and the endogenous default barrier approach represent meaningful values for all of the companies. More precisely, the default-to-debt ratio β_{ALG} ranges from a minimum of 0.503 to a maximum of 0.969, with an average value of 0.801. On the other hand, the minimum, maximum, and mean values of β_{END} are 0.438, 0.945 and 0.752, respectively. If estimates of the firm asset volatility and of the expected rate of return are compared, both methods provide virtually identical results; besides, they are typically higher than those provided by the standard ML approach. Going back to the instance of BASF AG in Figure 1, it can be observed that, in effect, both methods generate more rational results than does the standard ML approach. Moreover, analysis of the results for Bouygues SA in Figure 2 reveals an interesting feature: pseudo ML estimates in the case of a well-behaved log-likelihood function as the one of this company are similar to those provided by the standard ML approach. This issue is further explored in Table 2.3, where the main descriptive statistics for the difference between pseudo ML and standard ML parameter estimates are provided. Although the mean absolute difference between default-to-debt ratios for all companies is 0.431 (median of 0.099), the mean difference among the group of companies with the most reasonable β_{MLE} values (higher than 0.3 and lower than 1) is merely 0.044 (0.016).

Table 2.3 *Differences among parameter values*

	No.	Mean	Median	SD
		All Companies		
$\lvert\beta_{ALG} - \beta_{MLE}\rvert$	96	0.431	0.099	0.784
$\lvert\sigma_{ALG} - \sigma_{MLE}\rvert$	96	0.019	0.001	0.040
$\lvert\mu_{ALG} - \mu_{MLE}\rvert$	96	0.006	0.000	0.019
		$0.3 < \beta_{MLE} < 1.0$		
$\lvert\beta_{ALG} - \beta_{MLE}\rvert$	56	0.044	0.016	0.072
$\lvert\sigma_{ALG} - \sigma_{MLE}\rvert$	56	0.001	0.000	0.002
$\lvert\mu_{ALG} - \mu_{MLE}\rvert$	56	0.000	0.000	0.000

This table provides the main descriptive statistics for the difference between pseudo ML and standard ML parameter estimates.

Previous results allow for several conclusions. (a) The standard ML approach does not represent a good candidate for the preferred method, as it often provides puzzling results. (b) In cases in which the log-likelihood is well-behaved and the standard ML approach generates rational values, the pseudo ML approach leads to similar results. Notwithstanding, the pseudo ML approach provides reasonable values, even when the standard ML approach seems to fail. (c) The endogenous default-to-debt ratio could be naturally thought of as a lower bound for the true value. In other words, factors that differ from the interest of equity holders (e.g. debt covenants, liquidity restrictions, bankruptcy codes) – if present – are expected to move the default barrier upwards.[33] I find further support for the pseudo ML approach in view of this argument, as not only is β_{ALG} higher than β_{END} on average, but this seems to be the general rule on a firm-by-firm basis: it holds for 94 out of the 96 companies in the sample considered. Yet, β_{ALG} values within reasonable bounds are only a minimum requirement. Assessment of the real precision – and utility – of the proposed method, requires an investigation of its ability to generate sensible credit spread estimates as well; this point is addressed in the next sub-section.

2.7.2 Implied credit spreads

Results on model implied credit spreads (ICS) on the basis of the different estimation methods are provided in Table 2.4, along with the corresponding CDS spreads. It can be observed that, in fact, replication of CDS spreads is highly influenced by the chosen estimation method. Although the cross-sectional mean level of CDS spreads (71.82 bp) is almost fully matched by ICS_{ALG} estimates (71.34 bp), this does not hold for other options that either underestimate (45.49 bp for ICS_{END} and 41.07 bp for ICS_{KMV}) or considerably overestimate (194.98 bp for ICS_{MLE} and 223.29 bp for ICS_{P}) CDS premia. In addition, ICS_{ALG} have another desirable characteristic: contrary to other methods – particularly the standard ML approach and the KMV approach – ICS_{ALG} completely follow the pattern and the level of CDS spreads over different rating categories.[34]

[33] A default barrier below the endogenous value would need to be interpreted as the result of equity holders being forced to continue running a company, even when they wish to declare the firm bankrupt. Limited liability of equity holders rules out this situation, however.

[34] In order to insure that overall conclusions are not affected by the specific choice of the recovery rate, I have replicated the analysis by fixing the recovery rate at 51.31%, as in Huang and Huang (2003), and by setting bankruptcy costs α equal to 0.3 as in Leland (2004). Results, not presented here, single out once again the best fit of ICS_{ALG} estimates

Table 2.4 *CDS spreads and ICS estimates*

	All	AAA-AA	A	BBB	BB
CDS	71.82	22.00	51.39	107.02	151.95
ICS_{MLE}	194.98	176.23	225.16	176.40	91.77
ICS_{ALG}	71.34	21.18	48.22	107.53	164.73
ICS_{END}	45.49	11.85	33.26	63.43	125.76
ICS_{KMV}	41.07	13.18	43.68	50.39	24.25
ICS_{P}	223.29	79.98	175.91	320.70	345.53

This table reports mean values for cross-sectional CDS spreads, along with model implied credit spread (ICS) based on the different estimation methods.

More formal, standard measures of price discrepancy between ICS and CDS series are summarized in Table 2.5. In particular, pricing errors are measured by: average basis – avb; percentage average basis – avb(%); average absolute basis – avab; percentage average absolute basis – avab(%); and root mean squared error – RMSE. Results confirm the initial conclusion set forth in Table 2.4; that is, among all possible estimation methods, the pseudo ML approach provides the best predictions on CDS spreads. Specifically, the ICS_{ALG} – CDS basis is, on average, -0.48 bp, suggesting that the ICS_{ALG} represent, in practice, an unbiased estimator of the CDS spread; furthermore, the mean absolute basis amounts to 43.01 bp. The second-best option corresponds to ICS_{END}, with an average basis of -26.33 bp and an average absolute basis of 46.88 bp. The systematic underestimation of credit spreads, as suggested also by results in Table 2.4, is, however, consistent with the underestimation of the default barrier discussed in previous sub-section. The third-best option seems to be provided by KMV’s default point: average basis of -30.75 bp and average absolute basis of 58.66 bp. As a counterpart, pricing errors in the light of other methods are sizable, with ICS_{MLE} and ICS_{P} far above CDS spreads (average basis of 123.16 and 151.47 bp, respectively). The overall conclusion is clear support for the pseudo ML estimation method in comparison with other methods, and particularly in comparison with the standard ML approach. Among all possible options, the endogenous default barrier method represents the second-best option.

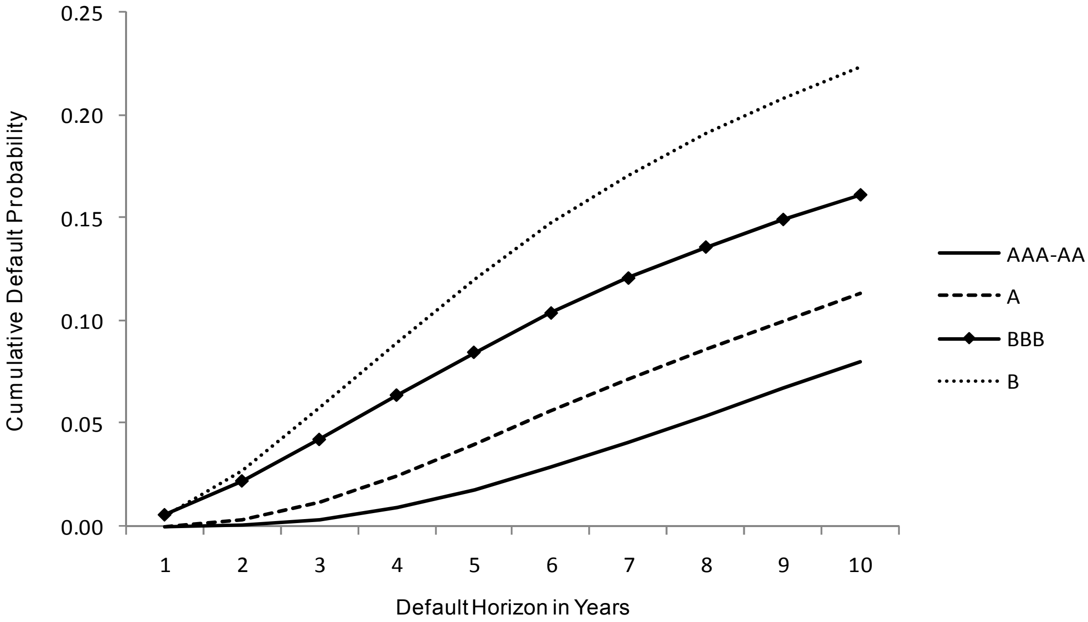
Table 2.5 *Measures of Pricing Discrepancy*

	avb	avb (%)	avab	avab (%)	RMSE
ICS_{MLE}	123.16	4.02	158.34	4.44	174.66
	(49.95)	*(1.02)*	*(82.37)*	*(1.18)*	*(92.33)*
ICS_{ALG}	-0.48	0.11	43.01	0.76	52.16
	(-8.61)	*(-0.21)*	*(27.03)*	*(0.57)*	*(32.72)*
ICS_{END}	-26.33	-0.23	46.88	0.76	54.94
	(-25.07)	*(-0.55)*	*(32.88)*	*(0.71)*	*(38.04)*
ICS_{KMV}	-30.75	-0.26	58.66	0.89	66.93
	(-29.09)	*(-0.69)*	*(38.41)*	*(0.86)*	*(42.44)*
ICS_{P}	151.47	2.97	156.65	3.03	177.46
	(98.24)	*(2.10)*	*(105.60)*	*(2.10)*	*(124.28)*

This table provides cross-sectional mean (median) values of the standard measures of credit spread differentials between ICS and CDS series: average basis – avb; percentage average basis – avb(%); average absolute basis – avab; percentage average absolute basis – avab(%); and root mean squared error – RMSE.

As a final illustration of the empirical performance of the pseudo ML procedure, I assess risk-neutral default probabilities for time horizons ranging from 1 to ten 10 years. Risk-neutral default probabilities across the different rating categories, and on a cross-sectional basis, are presented in Figure 2.3. Following economic intuition, the estimated probabilities of default increase with both the time horizon and the average credit riskiness. By way of example, the estimated risk-neutral default probabilities for the 5-year horizon are: 1% for an AAA-AA rated company, 2.8% for A, 5.2% for BBB, and 9.3% for BB.

Figure 2.3. *Risk-Neutral Default Probabilities*



This figure represents cross-sectional risk-neutral default probabilities by rating category, calculated on the basis of the pseudo ML estimates, and for a default time horizon ranging from 1 to 10 years.

2.7.3 Robustness check

In order to attain robustness, it seems suitable to verify whether the estimation method suggested in this chapter is also capable of providing reasonable results for other structural models, and not merely for the one considered in this study. Of particular interest is the down-and-out call (DOC) barrier option model discussed by Brockman and Turtle (2003), Predescu (2005), and Wong and Choi (2009). Analytical expressions for the DOC pricing equation and the first derivative of the element-by-element transformation are given in Appendix D.[35]

Results from both the standard and pseudo ML estimation method are provided in Table 2.6. In line with Wong and Choi (2009), standard likelihood maximization results in

[35] Maturity of the DOC option is chosen to correspond to the average maturity of the firm's total liabilities of 3.38 years as reported in Stohs and Mauer's (1996) empirical study. In addition, this is close to the hypothetical average maturity of the company's debt of 3.67 years, calculated by following the assumption made in this chapter that the company's debt at each instant consists of ten bonds: one with a maturity of one year and principal equal to STL, and nine with maturity ranging from two to ten years, each with principal equal to 1/9 of LTL. The corresponding risk-free rate is determined by interpolating between 3- and 4-year swap rates.

unreal default-to-debt ratios for a substantial number of companies. Namely, this parameter is higher than the one for as many as 39 companies (41% of the sample), with a maximum of 4.410. On the other hand, pseudo ML estimates represent reasonable values that fall in the range of 0.156 to 0.891, with a mean value of 0.616. Although estimated values for the default-to-debt ratio are lower than those provided in Table 2, this should be interpreted as a product of the differences in the underlying structural models. In fact, results in this case are consistent with those in Predescu (2005): in the light of the same DOC model, while using additional data on CDS spreads, she reports a mean default-to-debt ratio of 0.591. All things considered, it can be concluded that the proposed method leads to more meaningful results than does the standard ML approach, irrespective of the underlying model.

Table 2.6 *Parameter estimates: BT*

Panel A. Descriptive Statistics

	Mean	Median	SD	Min	Max
Standard ML Estimation					
β_{MLE}	1.077	0.934	0.615	0.178	4.410
σ_{MLE}	0.151	0.137	0.091	0.042	0.578
μ_{MLE}	0.001	0.002	0.059	-0.177	0.161
Pseudo ML Estimation					
β_{ALG}	0.616	0.627	0.125	0.156	0.891
σ_{ALG}	0.170	0.160	0.093	0.042	0.578
μ_{ALG}	0.008	0.002	0.068	-0.177	0.243

Panel B. Distribution of Default-to-Debt Ratios

Range	β_{MLE}	β_{ALG}
[0.0 - 0.1]	0	0
(0.1 - 0.2]	1	1
(0.2 - 0.3]	0	0
(0.3 - 0.4]	0	7
(0.4 - 0.5]	2	3
(0.5 - 0.6]	5	26
(0.6 - 0.7]	7	37
(0.7 - 0.8]	20	19
(0.8 - 0.9]	9	5
(0.9 - 1.0]	13	0
(1.0 - 1.1]	10	0
(1.1 - 1.2]	9	0
> 1.2	20	0

This table reports, for the case of the Brockman and Turtle's (2003) model, main descriptive statistics of the parameter estimates (Panel A), along with the distribution of default-to-debt ratios (Panel B). Results from the standard ML approach and the pseudo ML approach are considered.

2.8 Conclusions

In this chapter a new approach for the estimation of structural credit risk models with an exogenous default barrier is presented. Specifically, an iterative algorithm that provides pseudo ML estimates of the default barrier and estimates of the value, volatility, and expected return on the firm's assets is introduced. This new approach is tested empirically on the basis of an international sample of 96 companies. Taking as the reference credit risk model, the modified version of Leland and Toft's (1996) model suggested by Forte (2009), it is confirmed that standard maximization of the log-likelihood function often results in unreal barriers. On the contrary, the pseudo ML approach proposed in this chapter generates reasonable values that fall in the range of 50.3% to 96.9% of the nominal debt value. In terms of CDS spread estimation, theoretical credit spreads based on the suggested method generate the lowest pricing errors when compared to the other options that are usually considered when specifying the default barrier: standard ML estimate, endogenous value, KMV's default point, and principal value of debt.

Chapter 3

Structural Imbalances in the Credit Default Swap Market: Empirical Evidence

3.1 Introduction

A widely accepted finding in empirical literature on corporate bonds is that corporate bond yield spreads are substantially affected by non-default components such as: taxes, illiquidity, and different market microstructure effects (Elton et al., 2001; Longstaff et al., 2005; Ericsson and Renault, 2006; Chen et al., 2007). In contrast, Credit Default Swap (CDS) prices have often been labeled as a "near-ideal" measure of default risk due to their theoretical design. CDS represents a type of bilateral insurance contract that provides protection against default by the particular reference entity (company or sovereign). As such, a premium that the buyer of the protection pays to the seller – the CDS spread, is directly linked to the credit quality of the reference entity and is expected to provide a "pure" measure of credit risk.

This argument has been used in several studies and CDS spreads emerged as a preferred market benchmark for credit risk when analyzing the bond market or when testing the performance of structural credit risk models (Longstaff et al., 2005; Blanco et al., 2005; Ericson et al., 2007; Saita, 2006; Han and Zhou, 2008; Nashikkar et al., 2008). Few recent studies, however, demonstrate that CDS spreads do in fact contain non-default components. Tang and Yan (2007) explicitly consider different facets of liquidity and find that its effect on the CDS premium is significant and on par with that of Treasury and corporate bonds. Bongaerts et al. (2010) propose a theoretical asset pricing model that allows for liquidity effects, and find evidence of liquidity premium earned by the protection seller. Finally, recent financial turmoil episodes point out that CDS spreads are not free of non-default components and that liquidity should eventually be one of the most important non-default drivers of CDS spreads.

Liquidity is an obscure concept and there is no universally accepted liquidity measure or definition. In general, liquidity could be defined as the ability of market participants to trade large quantities of asset rapidly without affecting the asset's price. Although the liquidity phenomenon has been studied extensively in the equity and bond markets, much less is known about its effects in the CDS market. The CDS market has its distinguishing features, however. CDSs are contracts, they are traded in the opaque over-the-counter (OTC) market, and the participants in the CDS market are mainly insiders. In the context of the CDS market, liquidity has so far usually been proxied and controlled for by the relative bid-ask spread.[36] Still, liquidity has many distinctive aspects, and in order to reveal the driving forces of CDS spreads it is necessary to conduct detailed analysis on each of them.

This chapter treats one particular aspect of liquidity – demand-supply imbalance. Fitch Inc. (2004) reports that CDS market at times seems to be subject to structural imbalances as protection buyers tend to exceed protection sellers. This intuitively implies that in the periods of scarcity of sellers, buyers will be willing to bid higher prices whereas the sellers will continue to be concerned about the easiness with which their position could be offset after the transaction has been completed and will thus demand a liquidity premium. As such, demand-supply imbalance should affect CDS prices and represent one of the important aspects of liquidity. The analysis made in this chapter contributes to the existing literature by

[36] Tang and Yan (2007) in addition to relative bid-ask spread consider other liquidity measures (volatility-to-volume, number of outstanding contracts, trades to quotes) some of them taken directly from the literature on stock market liquidity. Chen et al., 2005 approximate liquidity by the frequency of price changes.

providing empirical evidence of the existence of structural demand-supply imbalances in the CDS market and by illustrating its effect on the CDS spread dynamics.

In order to investigate the effect of demand-supply imbalances in the CDS market, it is necessary to relate it to the part of the CDS premium not related to fundamentals. Theoretically, variables perceived by structural models (market value of the firm's assets, volatility, leverage, and risk-free rate) should be the main determinants of credit spreads. In an attempt to explain determinants of CDS spread dynamics, the majority of empirical studies follow the approach widely adopted in the corporate bond literature and carries out a linear regression on key variables suggested by economic theory (Aunon-Nerin, 2002; Blanco et al. 2005; Abid and Naifar, 2006; Ericsson et al., 2007; Greatrex, 2009).[37] Structural credit risk models, however, impose a highly non-linear functional relationship between key variables and credit spreads. Following such reasoning, another option lies in the theoretical credit spreads that in a single measure, in a non-linear way, jointly account for all key variables.

In this chapter fundamentals are accounted for through stock market implied credit spreads (ICSs). These are estimated using pseudo ML methodology developed in previous chapter, using data from stock market only and not relying on any additional information from other credit-sensitive markets (CDS or bond market). Obtained ICSs in fact support the usefulness of structural models: ICSs can explain substantial part of the cross-sectional variation in the CDS spread levels, and theoretical parity relationship between CDS spreads and ICSs holds on average as an equilibrium condition. In this way it is possible to isolate the component of CDS spreads that is specific solely to the credit market (both on aggregate and firm-specific levels), and to relate this component to different imbalance measures.

[37] Empirical literature has been so far mainly oriented towards explaining the determinants of corporate bond spreads and corporate bond spread changes (Collins-Dufresne et al, 2001; Avramov et al. 2007; Blanco et al. 2005). The literature on CDSs is of smaller scope but increasingly growing.

In this chapter the economic and statistical significance of different imbalance measures on the CDS spread dynamics is empirically demonstrated, pointing out that CDS spreads reflect not only a pure credit risk premium, but also a compensation for the anticipated costs of unwinding the position of protection sellers. Namely, CDS changes not related to fundamentals (CDS innovations) are positively related to an increase in the number of bids as regards offers, especially during turbulent times. The evidence is corroborated on the representative set of 163 companies (92 European and 71 North American) during a relatively long period for CDS market, 2002-2008, including recent financial crisis.

The remaining part of the chapter is organized as follows. Section 3.2 describes the data set. Section 3.3 describes the methodology for extracting the ICSs and assesses the fit of the ICSs to market CDS spreads. Section 3.4 introduces different imbalance measures. Section 3.5 presents main empirical results over different methodological approaches. Section 3.6 concludes.

3.2 Data

Data on Credit Default Swap spreads is provided by GFI, an inter-dealer broker (IDB) in credit derivatives.[38] The GFI data comprise information on: intraday quotes and trades, reference entity, seniority of the reference issue and maturity.[39] There is no trade direction indicator, and no information on size. The initial data set contains quotes for 1,688 reference entities (54 sovereigns and 1,634 companies), out of which 643 (38.1%) are European and

[38] The GFI CDS database has been previously used by Hull et al., (2004), Predescu (2005), Saita (2006), and Nashikkar et al., (2008), among others.

[39] The data refer to actual executable and executed market prices where dealers commit capital. As such, the data reflect market sentiment rather than indications. The data are previously corrected for errors using both experienced data analysts and statistical cleansing algorithms by GFI.

1,045 (61.9%) are North and South American. The time period spans from January 2002 to December 2008.[40]

Although the number of reference entities is relatively high for the overall period, the number of reference entities with available quote entries in any given year is much smaller and amounts to 1,046 (404 European and 642 North and South American) on average. Interestingly, the number of reference entities in the European market was increasing steadily during the period examined, reaching the maximum of 469 in 2008. The number of reference entities in North and South American market was increasing till 2005 and onward declined successively, reaching the minimum of 584 at the end of the sample period (see, Figure 3.1).

Figure 3.1 *No. of reference entities per year and region*

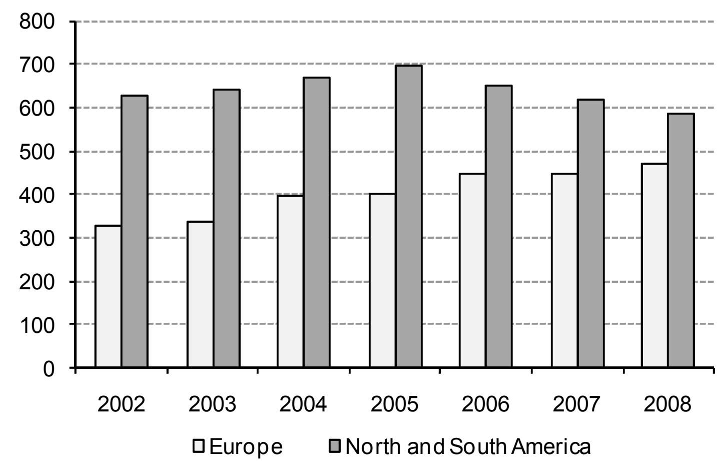


Figure 3.1 shows the total number of reference entities in the initial sample (including sovereigns, financial and non-financial companies, publically and not publically traded companies) with available quote entries. The data are reported per year and per geographical region.

The initial data set contains 2,265,164 intra-day quote and trade entries expressed in basis points. However, there is substantial misbalance between the considered geographical

[40] On the initiative of the International Swaps & Derivatives Association (ISDA), the "Big-Bang" protocol with new CDS convention - the Standard North American Contract (SNAC), was launched in April 2009. For the European region the standardization began from June 2009. These events therefore do not affect the data in the sample considered.

regions. As much as 72.5% (1,641,326) refer to European, whereas just 27.5% (623,838) to North and South American reference entities. Moreover, the two geographical regions differ substantially in the distribution of quote and trade entries on a yearly basis. That is, the number of quotes and trades for the European region was increasing steadily till 2007, whereas, the number of quotes and trades for the American region peaked in 2005 (see Figure 3.2).

Figure 3.2 *No. of quote and trade entries per year and region – initial data set*

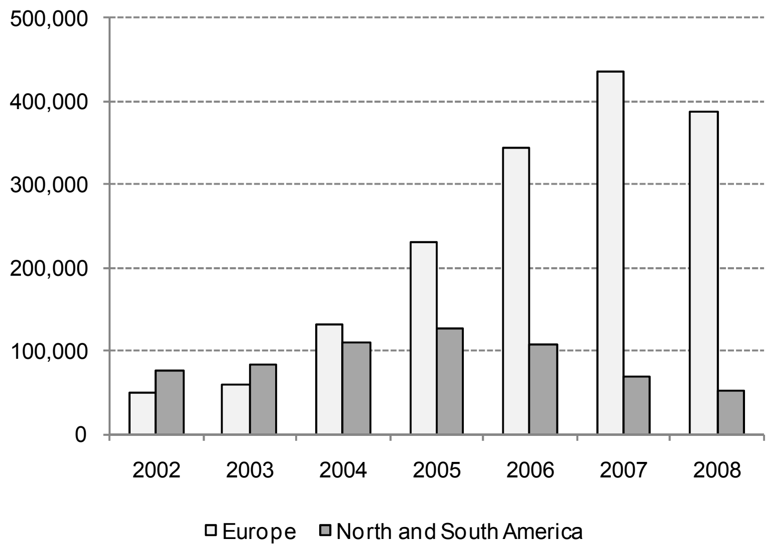


Figure 3.2 shows the total number of quote and trade entries per year and per geographical region for the initial sample.

In this study I consider only the most liquid, 5 year maturity contracts, (86.3% of the available entries), and contracts drowned on senior unsecured debt (90.9% of the available entries). For the European market I consider only euro-denominated contracts, and for the American market only dollar-denominated CDS contracts. Given that further analysis requires data on market capitalization, sovereigns and companies that are not publicly traded are excluded from the sample, whereas companies in the banking and finance sector are excluded due to their different capital structure. Companies from GFI database are manually matched (by company name and industry) with the Datstream database, and several companies are further excluded due to the lack of the data.

Given the purpose of the study and in order to facilitate cross-sectional and time-series comparison, several additional criteria have been applied. First, with the aim of considering as large time period as possible while insuring homogeneity, I include only companies that are active in the CDS market from 2002 till the end of 2008. In other words, companies that appear in the sample from 2003 or any other subsequent year, and companies that have disappeared due to bankruptcy or merger with other companies, are excluded from the sample. Second, only companies with relatively active CDS contracts are considered: all the companies with 0 trades in any of the considered years, and companies with quotes and trades available for less than 5% of the trading days in any of the considered years are initially excluded.

After filtering the initial data set, the final sample comprises 163 companies: 92 European and 71 North American. The main characteristics of the companies considered are presented in Table 3.1. The average European company in the sample has market capitalization of 16 billion Euros, leverage of 0.51, and historical equity volatility of 37%. On the other hand, the average North American company has market capitalization of 22.4 billion Dollars, leverage of 0.49, and equity volatility of 0.39%. Leverage is defined as the ratio of the book value of total liabilities over the sum of market value of equity and book value of total liabilities. Data on market capitalization and book value of liabilities have been downloaded from Datastream.

Table 3.1 *Main characteristics of the companies in the sample*

Panel A: Descriptive statistics for European companies

Statistic	MC in m €	Equity Volatility	Leverage
Mean	16,027.29	0.37	0.51
Median	9,455.98	0.36	0.51
St. Dev.	15,865.64	0.09	0.20
Min	1,099.81	0.15	0.05
Max	70,441.91	0.71	0.93

Panel B: Descriptive statistics for North American companies

Statistic	MC in m $	Equity Volatility	Leverage
Mean	22,445.40	0.39	0.49
Median	12,368.70	0.36	0.50
St. Dev.	34,536.19	0.10	0.17
Min	985.39	0.23	0.13
Max	217,978.56	0.79	0.94

This table reports the main descriptive statistics on a cross-sectional basis for the final set of 163 non-financial companies (92 European and 71 North American). MC refers to market capitalization in million Euros for the European region (Panel A) and million Dollars for the North American region (Panel B). 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 over the proxy for the market value of the firm (i.e. sum of market value of equity and book value of total liabilities).

One important characteristic of this final set of companies is that the homogeneity of the sample is insured for the entire 2002-2008 period, as all considered companies are present with quote entries in every year during the sample period. In total, the final sample contains 758,787 intra-day quote and trade entries: 622,488 (82%) for the European region and 136,299 (18%) for the North American region. It is worth noting that despite the applied filtering, the final sample turns out to be quite representative: it contains around 1/3 of all initially available quote and trade entries during the 2002-2008 period, and it follows the pattern of the distribution of initially available quotes and trades over different years and regions, as previously discussed (see Figure 3.3).

Figure 3.3 *No. of quote and trade entries per year and region – final sample*

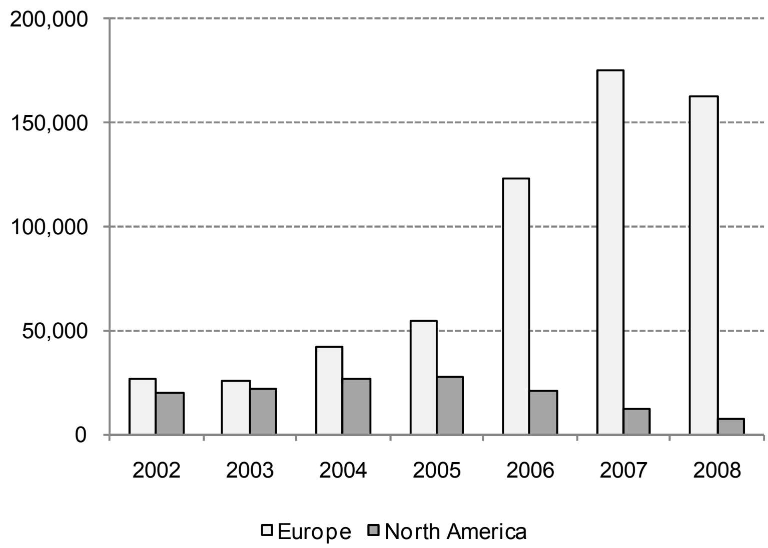


Figure 3.3 shows the total number of quote and trade entries per year and per geographical region for the final sample.

Given that the dataset contains only intra-day bid and ask quotes, daily CDS spread observations are constructed on the end-of-day basis in the following manner: if on a given day both bid and ask quotes are present, CDS spread refers to the midpoint of the last bid and last ask quote; if on a given day only bid (ask) quotes are present, CDS spread refers to the midpoint of the last bid (ask) on a given day and the most recently available ask (bid) quote entry. In this way, for the selected reference entities there are 124,391 available daily observations in total, or, 763 per company on average. This means that for an average company in the sample, a new quote is available approximately every second or third trading day. Still, there are substantial differences between the companies, with minimum of 12% and maximum of 97% of the trading days with quotes availability. The missing data are filled in assuming the last observable CDS spread (i.e. the most recent quote) following the reasoning that if there is no new bid or ask quote, there is no new information leaked in the market for the specific company.

Finally, it can be argued that it is better to use actual transactions prices instead of composed CDS spreads. However, transactions in the CDS market are still relatively scarce. This would imply a substantial reduction in the number of considered companies and a substantial reduction of the availability of CDS spread observations on a daily basis. By way of example, for the final sample the average quoting frequency per day is 399 whereas the trading frequency is only 33, i.e. every 12 quotes result in one trade. This is an important issue given that the effect of structural imbalances (and other aspects of liquidity) should be short-lived and it is therefore necessary to conduct the analysis on higher frequencies, such as daily and at most weekly. Most importantly, quotes are binding. Posted bid and ask quotes are firm and cannot be withdrawn once they are hit, that is, the issuer is obliged to trade at his quote. As such, composed CDS spreads represent a good approximation for the actual CDS prices.

In order to better capture the time-series variation in CDS spreads, fundamentals and imbalance factors, the overall period considered is further divided into three sub-periods: from the beginning of 2002 to mid-2003 (Period 1), from mid-2003 to mid-2007 (Period 2), and from mid-2007 till the end of 2008 (Period 3), as shown in Table 3.2. The first sub-period is characterized by credit market turbulence, high levels of CDS spreads, and the CDS market being in its development stage. Starting from the late 2001, the CDS market faced massive bankruptcies and other credit events such as the ones of Enron (December 2001), WorldCom (July 2002), Xerox (December 2002), and Conseco (August 2002). Global corporate default rates peaked in the second half of 2002, and substantially declined since the second half of 2003 (S&P Report, 2006).[41] The second sub-period is characterized by increased contract standardization followed by growing CDS market activity measured by the number of quotes and trades per day. Moreover, as argued by Imbierowicz (2009), CDS spreads were

[41] According to S&P Report (2006) no more than three corporate obligors referenced in synthetic CDOs have triggered credit events from the second half of 2003.

substantially lower from mid-2003, declining up until mid-2007 and the beginning of the recent subprime crisis. The third period is the period of the recent financial crisis and is of particular interest. In fact, the last sub-period includes significant events for the CDS market such as: freeze of the money market (August 2007), the collapse of Bear Stearns (March 2008) and the collapse of Lehman Brothers (September 2008).[42] In this way it is possible to conduct analysis and compare empirical findings between normal (Period 2) and stress (Period 1 and Period 3) regimes.

Table 3.2 *Sub-periods*

Period	From	To
Period 1	January 2002	June 2003
Period 2	July 2003	June 2007
Period 3	July 2007	December 2008
All	January 2002	December 2008

Table 3.2 illustrates the division of the overall 2002-2008 sample period into three sub-periods.

Respecting the abovementioned division into three distinctive sub-periods, Table 3.3 provides the main characteristics of the final data set. In total, there are data on 700,512 quotes and 58,275 transactions. Therefore, out of all entries, transactions are represented with only 7.7%. Out of available quotes 463,535 (66.2%) are two-sided quotes, 147,226 (21%) are net bid quotes, and 89,751 (12.8%) are net ask quotes.[43] In general there are more bid quotes (protection buyers) than ask quotes (protection sellers), which is already an indication that CDS market is likely to be subject to structural imbalances. For the two different geographical regions, the distribution of quotes on: two-sided, net bid, and net ask quotes, is approximately equal, with bid quotes surpassing ask quotes. However, there is a substantial regional difference as to market activity across the three sub-periods, measured by the

[42] The interbank credit crunch was initiated on the 9th of August 2007 when the LIBOR-OIS spread jumped 25 basis points above its 11 bps average.
[43] Two-sided quotes are joint observations of bid and ask quotes at the same point of time.

number of quotes and trades per day. Within the European region the number of quotes and trades per day has been rising constantly, reaching the maximum of 656 quotes and 35 transactions in Period 3. In contrast, within the North American region this measure of market activity has substantially declined in the last sub-period: from 227 quotes and 27 transactions per day in Period 2, to only 25 quotes and 5 transactions in Period 3.

Table 3.3 *Quote and trade entries per period and region – final sample*

Panel A: Quote and trade entries for European companies

Period	NNBQ		NNAQ		NTSQ		NQ		NT	
	total	per day	total	per day	total	per day	total	per day	total	per day
Period 1	9,566	25	8,443	22	21,028	56	39,037	104	5,239	14
Period 2	63,913	64	33,833	34	196,721	197	294,467	294	25,439	25
Period 3	48,480	130	30,215	81	166,528	445	245,223	656	13,083	35
All	121,959	70	72,491	41	384,277	219	578,727	330	43,761	25

Panel B: Quote and trade entries for North American companies

Period	NNBQ		NNAQ		NTSQ		NQ		NT	
	total	per day	total	per day	total	per day	total	per day	total	per day
Period 1	8,342	22	6,684	18	13,145	35	28,171	76	2,811	8
Period 2	14,154	38	9,559	26	60,585	163	84,298	227	9,984	27
Period 3	2,771	7	1,017	3	5,528	15	9,316	25	1,719	5
All	25,267	15	17,260	10	79,258	46	121,785	70	14,514	8

Panel C: Quote and trade entries for the overall sample

Period	NNBQ		NNAQ		NTSQ		NQ		NT	
	total	per day	total	per day	total	per day	total	per day	total	per day
Period 1	17,908	48	15,127	40	34,173	91	67,208	178	8,050	21
Period 2	78,067	78	43,392	43	257,306	257	378,765	378	35,423	35
Period 3	51,251	137	31,232	84	172,056	460	254,539	681	14,802	40
All	147,226	84	89,751	51	463,535	264	700,512	399	58,275	33

This table reports the number of quote and trade entries for the overall final sample and for the three distinctive sub-periods. Panel A reports the number of quote and trade entries for the 92 European companies, Panel B for the 71 North American companies and Panel C for the overall sample of 163 companies. NNBQ refers to the number of net bid quotes, NNAQ to the number of net ask quotes, NTSQ to the number of two-sided quotes, NQ to the total number of quotes, and NT to the number of transactions.

3.3 Fundamentals and CDS spreads

In order to isolate the effect of structural imbalances on CDS spreads, it is necessary to control for the fundamental variables driving credit risk. Usually, in the literature, variables suggested by structural models of default (market value of the firm's assets, volatility, leverage, and risk-free rate) are considered as fundamental determinants of credit risk. In most empirical studies these variables are taken separately in a linear manner to account for changes in credit risk (Collins-Dufresne et al, 2001; Aunon-Nerin, 2002; Avramov et al. 2007; Blanco et al. 2005; Ericsson et al., 2007; Abid and Naifar, 2006; Tang and Yan, 2007; Greatrex, 2009). Contrary to this approach, I consider just one variable to account for the fundamentals: the theoretical credit spread implied from the stock market (ICS). The advantages of this approach are twofold. First, theoretical credit spreads in a single measure account for the key variables suggested by the economic theory to be the main determinants of credit risk, simultaneously respecting their highly non-linear functional interrelationship. Second, theoretical ICSs can be directly confronted and contrasted to CDS spreads as both measures represent alternative proxies for the same latent variable – the "pure" credit spread.

To be precise, the theoretical credit spread is determined on the basis of the modified version of the structural model of Leland and Toft (1996) suggested by Forte (2009), as the function of the firm's asset value and other variables necessary to specify the model (risk-free rate, volatility, default barrier and recovery rate). Unobservable set of variables (firm's asset value, volatility, and default barrier) are estimated using the pseudo ML approach proposed in the previous chapter. This method consists of an iterative algorithm applied to the log-likelihood function for the time series of equity prices. One main characteristic of the proposed procedure is that the estimation relies only on readily available data from the stock market and a small subset of balance sheet and income statement items, but not on additional information from other credit-sensitive markets (bond or CDS market).[44] A direct implication of this approach is that ICSs are completely independent from the CDS market dynamics. The proxy chosen for the risk-free rate in the structural model is the swap rate. The model considers 1-10 year swap rates implicitly taking into account the term structure of interest rates. The recovery rate is set to 40% in line with the studies of Covitz and Han (2004), Altman et al., (2005) and the industry practice.[45]

Final results on the volatility and the default barrier parameter estimates are shown in Table 3.4. For European companies, the mean cross-sectional estimate of the firm's asset value volatility is 16.86% and the mean default-to-debt ratio is 0.73. For North American companies, the mean estimate of the firm's asset value volatility is 18.44% followed by the mean default-to-debt ratio of 0.78. The dispersion of the estimated default-to-debt ratios for both set of companies is quite similar, ranging from the minimum of 0.45 and 0.55 to the maximum of 0.91 and 0.93 for European and North American companies, respectively. As exemplified in the previous chapter, the pseudo ML procedure assures default-to-debt ratios for all companies in the sample to fall within reasonable bounds.

Table 3.4 *Parameter estimates*

Panel A: European companies			**Panel B:** North American companies		
Statistic	Firm's Asset Value Volatility	Default barrier parameter	Statistic	Firm's Asset Value Volatility	Default barrier parameter
Mean	0.17	0.73	Mean	0.18	0.78
Median	0.16	0.74	Median	0.17	0.78
SD	0.07	0.08	SD	0.07	0.07
Min	0.02	0.45	Min	0.04	0.55
Max	0.42	0.91	Max	0.42	0.93

This table reports the main descriptive statistics for the firm's asset volatility and the default barrier parameter estimates for a cross-section of European (Panel A) and North American (Panel B) companies.

[44] The subset of balance sheet and income statement items used in the estimation include: short and long-term liabilities, interest expenses and cash dividends. Data on these items is downloaded from Datastream.
[45] The analysis is verified for different specifications of the recovery rate.

Summary statistics for CDS spreads and ICSs on a cross-sectional basis are provided in Table 3.5. For the entire sample, the average CDS spread for European companies was 103.31 bp and for North American companies 123.89 bp. On average, ICSs underestimate observable CDS spreads. The mean ICS for European companies was 93.01 bp and for North American companies 88.28 bp. There is also a significant time-series variation in CDS spreads, as well as in ICS discrepancy. As expected, the discrepancy is higher during stress periods (Period 1 and Period 3) being particularly high during the last subprime crisis period, and much lower during the normal period (Period 2).

Table 3.5 *Summary Statistics for CDS spreads and ICS estimates*

Panel A: CDS spreads and ICS for European companies

Period	CDS			ICS		
	mean	median	sd	mean	median	sd
Period 1	158.65	92.40	166.72	140.06	87.95	133.21
Period 2	70.80	43.25	85.09	75.51	46.92	101.35
Period 3	137.36	93.99	121.94	93.92	38.36	161.34
All	103.31	69.46	93.81	93.01	57.37	102.37

Panel B: CDS spreads and ICS for North American companies

Period	CDS			ICS		
	mean	median	sd	mean	median	sd
Period 1	175.22	106.54	155.48	116.90	81.98	106.11
Period 2	93.95	47.07	112.93	73.20	35.37	94.47
Period 3	158.00	100.42	161.31	102.56	31.25	171.32
All	123.89	70.59	120.91	88.28	49.04	100.52

This table reports main cross-sectional descriptive statistics for CDS spreads and model implied credit spreads (ICS) for the overall sample and across three sub-periods considered. Panel A and Panel B report CDS spreads and ICSs for European and North American companies, respectively.

More formal measures of pricing discrepancy: the average basis - *avb*, the average percentage basis - *avb(%)*, the average absolute basis - *avab*, the average absolute percentage basis – *avb(%)*, and the Root Mean Squared Error - *RMSE*, are presented in Table 3.6. For the overall period ICSs on average underestimate market CDS spreads by 10.3 bp within the

European region. It is worth noting that the overall fit for European companies is much better on average than for North American companies. Within the North American region ICSs underestimate observed CDS spreads by 35.61 bp on average. Finally, as expected, pricing errors are larger in times of credit market turbulence and high levels of credit spreads, being the fit the best for Period 2 and the worst for Period 3.

Table 3.6 *Measures of CDS spreads and ICS pricing discrepancy*

Panel A: CDS spreads and ICS pricing discrepancy for European companies

Period	avb		avb (%)		avab		avab (%)		RMSE	
	mean	median	mean	median	mean	median	mean	median	mean	median
Period 1	-18.59	-9.25	0.02	-0.09	77.22	51.92	0.59	0.51	92.31	62.37
Period 2	4.72	2.11	0.12	0.02	38.44	23.83	0.67	0.61	45.77	29.09
Period 3	-43.43	-49.79	-0.48	-0.65	79.25	56.99	0.67	0.70	99.14	68.08
All	-10.30	-10.42	-0.03	-0.05	55.09	39.32	0.65	0.63	77.40	56.37

Panel B: CDS spreads and ICS pricing discrepancy for North American companies

Period	avb		avb (%)		avab		avab (%)		RMSE	
	mean	median	mean	median	mean	median	mean	median	mean	median
Period 1	-58.32	-42.23	-0.27	-0.40	83.32	61.02	0.52	0.50	95.91	72.18
Period 2	-20.74	-13.92	-0.23	-0.36	44.96	28.75	0.59	0.55	53.96	32.57
Period 3	-55.44	-49.82	-0.49	-0.65	97.71	65.33	0.72	0.73	116.71	78.39
All	-35.61	-23.32	-0.29	-0.40	63.68	44.59	0.60	0.59	85.39	61.40

This table provides mean and median values of the standard measures of credit spread differentials between ICS and CDS spread series: the average basis - *avb*, the average percentage basis – *avb(%)*, the average absolute basis - *avab*, the average absolute percentage basis – *avb(%)*, and the Root Mean Squared Error - *RMSE*. Measures of pricing discrepancy are reported for the overall sample and for three sub-periods considered. Panel A and Panel B report CDS spreads and ICS pricing differentials for European and North American companies, respectively.

In addition to firm-specific credit spreads, there is a possibility to consider CDS and ICS market indices. For that purpose I have constructed a CDS market index ($CDSm$) and its direct counterpart – an ICS market index ($ICSm$), as an equally weighted portfolio of all companies in the European or North American sub-samples (i.e. market wide portfolio). In this way, constructed historical synthetic time-series of regional $CDSm$ and $ICSm$ indices have an important desirable property: they are homogeneous across time. Although there is also a possibility to refer to iTraxx index, and CDX index here, I refrain from such approach for several reasons. First, iTraxx and Dow Jones CDX Indexes are available on regularly basis from mid-2004, what would imply a considerable reduction in the sample period that could be considered. Second, constituencies of the indexes have been changing over time, resulting in the loss of homogeneity. Figure 3.4 and Figure 3.5 illustrate constructed $CDSm$ and $ICSm$ global market indices for the European and North American regions, respectively. The overall sample is further divided based on the average rating of the obligor during the time period considered into investment and non-investment grade sub-samples, and corresponding investment grade and high-yield indices are constructed for the two distinctive geographical regions (see Figure 3.6 to Figure 3.7).

Figure 3.4 $CDSm$ *and* $ICSm$ *indices – overall European sample*

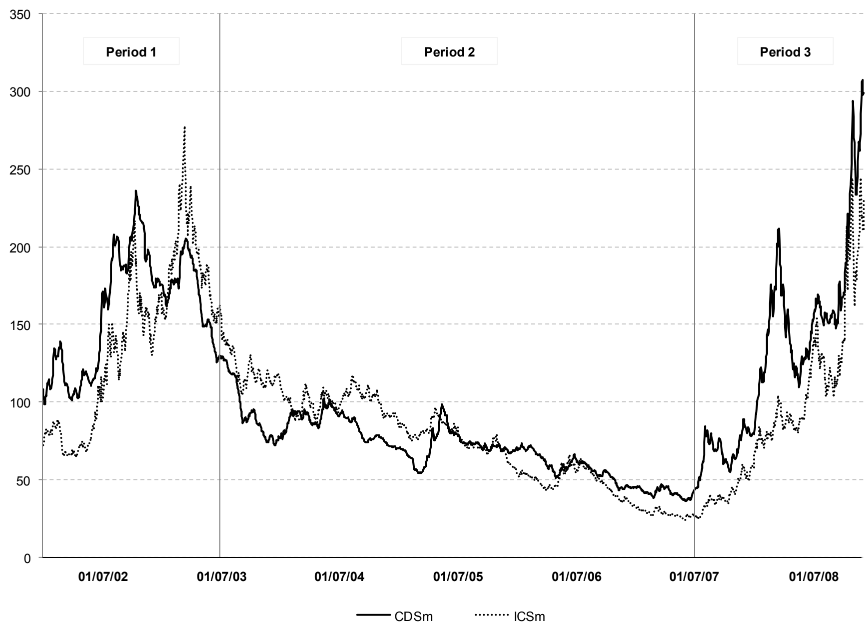


Figure 3.4 illustrates CDS market ($CDSm$) and ICS market ($ICSm$) indices for the European region. Indices are constructed as an equally weighted portfolio of all the companies in the sample.

Figure 3.5 *$CDSm$ and $ICSm$ indices – overall North American sample*

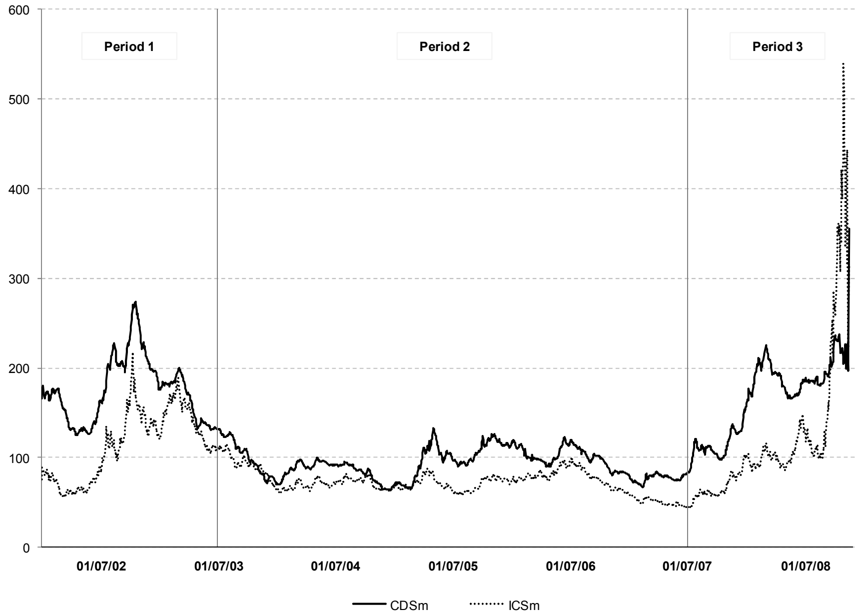


Figure 3.5 illustrates CDS market ($CDSm$) and ICS market ($ICSm$) indices for the North American region. Indices are constructed as an equally weighted portfolio of all the companies in the sample.

Figure 3.6 *$CDSm$ and $ICSm$ for investment-grade European companies*

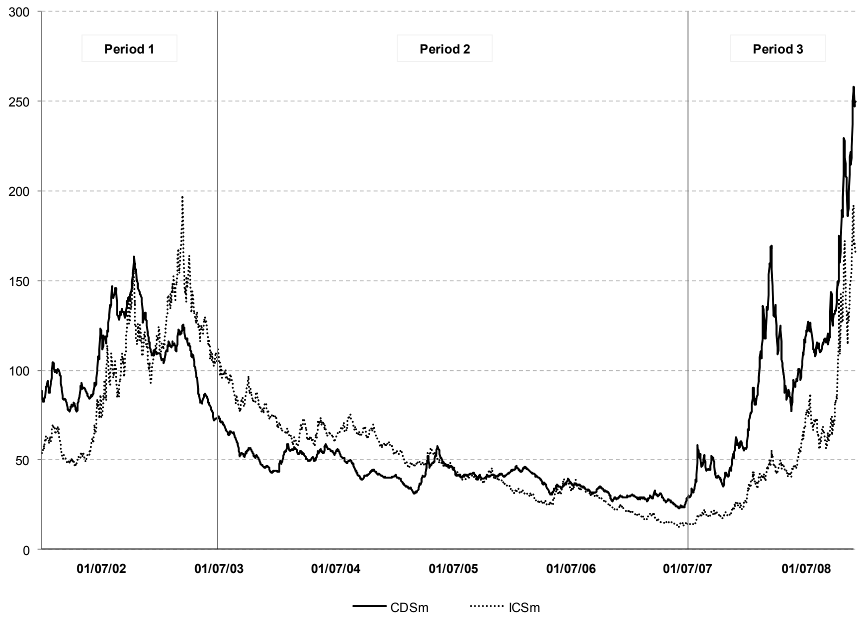


Figure 3.6 illustrates CDS market ($CDSm$) and ICS market ($ICSm$) investment grade indices for the European region. Indices are constructed as an equally weighted portfolio of those companies whose average rating during the time period considered falls within the investment grade category.

Figure 3.7 *$CDSm$ and $ICSm$ for non investment-grade European companies*

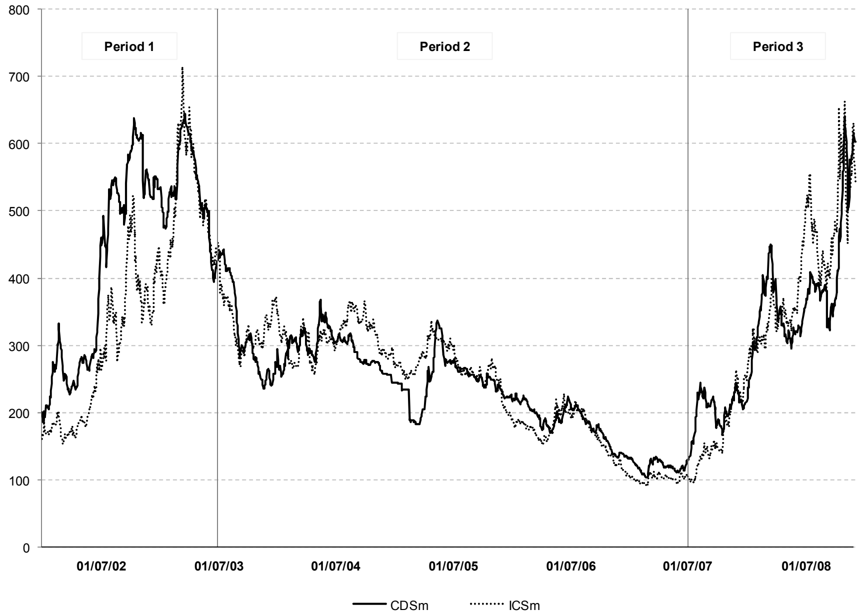


Figure 3.7 illustrates CDS market ($CDSm$) and ICS market ($ICSm$) high-yield indices for the European region. Indices are constructed as an equally weighted portfolio of those companies whose average rating during the time period considered falls within the speculative grade category.

Figure 3.8 *$CDSm$ and $ICSm$ for investment-grade North American companies*

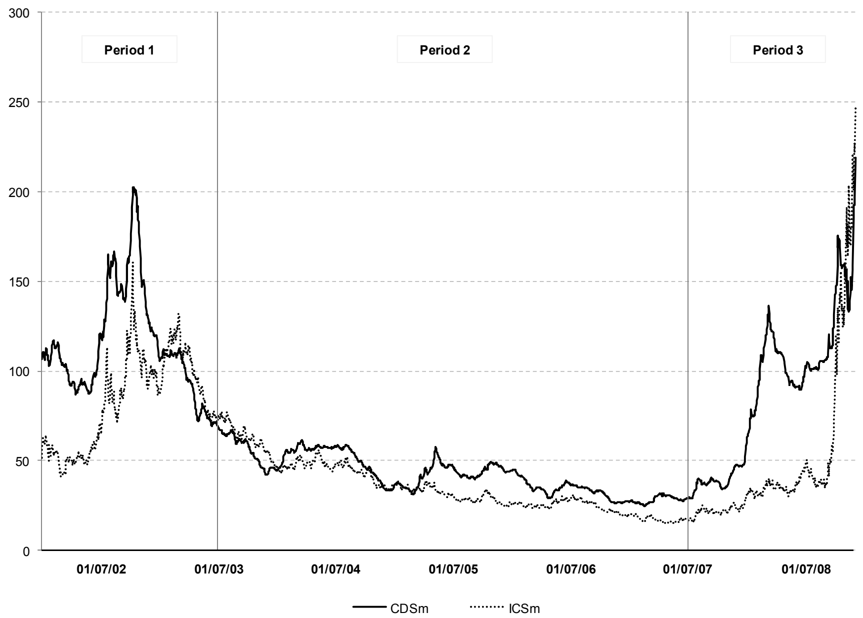


Figure 3.8 illustrates CDS market ($CDSm$) and ICS market ($ICSm$) investment grade indices for the North American region. Indices are constructed as an equally weighted portfolio of those companies whose average rating during the time period considered falls within the investment grade category.

Figure 3.9 *CDSm and ICSm for non investment-grade North American companies*

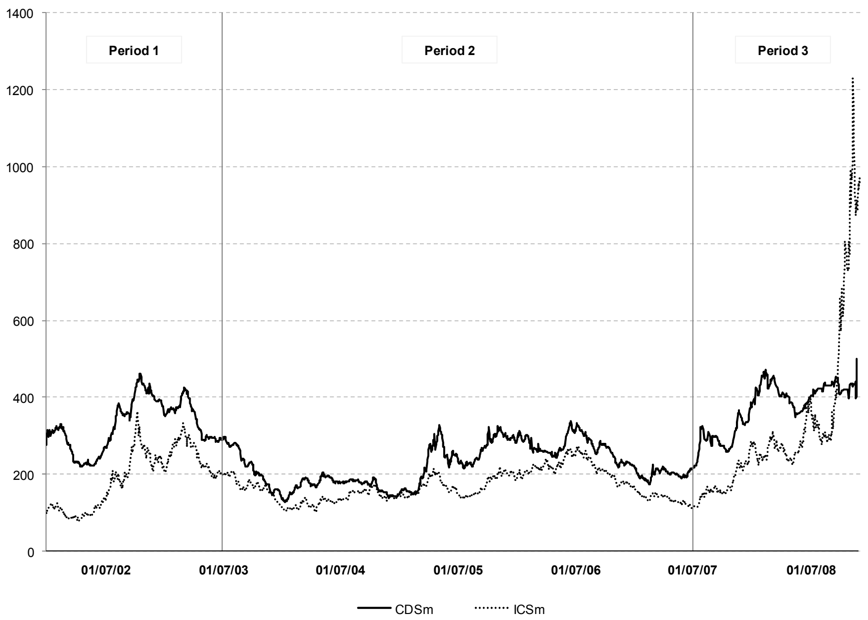


Figure 3.9 illustrates CDS market ($CDSm$) and ICS market ($ICSm$) high-yield indices for the North American region. Indices are constructed as an equally weighted portfolio of those companies whose average rating during the time period considered falls within the speculative grade category.

It is also possible to compare the levels of CDS spreads and ICSs between companies. Using daily CDS data, I run daily cross-sectional regressions of CDS spreads on its theoretical counterparts – ICSs:

$$CDS_i = \alpha + ICS_i + \varepsilon_i. \tag{3.1}$$

Daily cross-sectional regressions are conducted for the total of approximately 1,740 time points and separately for the European and North American regions. Results on the explanatory power, measured by the adjusted R^2 statistics, are presented in Table 3.7. For European companies, theoretical credit spreads are able to explain, on average, around 62.6% of the cross-sectional variations of the CDS spread levels. The standard deviation of the explanatory power is relatively low and amounts to 11.2%. Similar results are obtained for North American companies. Within this geographical region, ICSs are able to differentiate between firm-specific CDS spread levels slightly better with an average daily adjusted R^2 of 65.9% and a standard deviation of 9%. This means that the structural model, based on firm-specific fundamentals, is able to differentiate reasonably well between firm-specific CDS spread levels on a daily basis. Across considered sub-periods the average adjusted R^2 seems to be quite balanced. However, during the last sub-period, the explanatory power of ICSs was slightly higher than the average for the European companies and slightly lower than the average for the North American companies.

Table 3.7 *Explanatory power of ICS – daily cross-section*

Panel A: European companies

Statistics	Period 1	Period 2	Period 3	All
Mean	0.596	0.623	0.666	0.626
Median	0.622	0.633	0.676	0.650
Max	0.817	0.805	0.804	0.817
Min	0.256	0.361	0.262	0.256
SD	0.134	0.105	0.094	0.112

Panel B: North American companies

Statistics	Period 1	Period 2	Period 3	All
Mean	0.673	0.683	0.584	0.659
Median	0.683	0.687	0.581	0.667
Max	0.840	0.846	0.873	0.873
Min	0.440	0.500	0.394	0.394
SD	0.099	0.072	0.087	0.090

This table provides main descriptive statistics for the explanatory power (measured by adjusted R^2) of daily cross-sectional regressions of CDS spreads on its theoretical counterparts - ICSs. Panel A and Panel B refer to European and North American regions, respectively.

3.4. Imbalance Measures

In the literature no consensus yet exists on what precisely liquidity is and how it can be measured. In general, liquidity could be defined as the ability of market participants to trade large quantities of asset rapidly without affecting the asset's price. In fact, liquidity is characterized with multiple facets and cannot be explained with sufficient statistics (Tang and Yan, 2007). To date, liquidity has been studied extensively in the equity and bond markets, however, there is still not much evidence of the effect it has on the CDS market, traditionally believed to be less influenced by non-default components. Pioneering in this context, the studies of Tang and Yan (2007) and Bongaerts et al. (2010) provide evidence of the presence of liquidity effects in the CDS market. Tang and Yan (2007) consider different facets of liquidity (relative bid-ask spread, volatility-to-volume, number of outstanding contracts, trades to quotes) but carry out analysis using monthly frequency. Bongaerts et al. (2010) propose a theoretical asset pricing model that allows for liquidity effects, and find evidence of liquidity premium earned by the protection seller.

The analysis of liquidity issues in the CDS market is not straightforward. This market is opaque, over-the-counter market, and no trading party has full knowledge of the positions of others (Acharya and Bisin, 2010). Moreover, as opposed to stocks and bonds, CDS are bilateral contracts, and for CDS market to function at least some investors must have positive demand for credit protection, and at least some investors must be willing to sell credit protection. However, buyers and sellers do not tend to emerge at the same pace in the CDS market and, as reported by Fitch (2004), protection buyers often exceed protection sellers. Moreover, sellers of credit protection remain exposed to credit risk and will continue to be interested in the liquidity of the market after the transaction has been completed. In case of deficiency of sellers, it is likely that the seller will positively affect the mid-market quote by demanding a liquidity premium as a compensation for the lack of immediacy he would face for offsetting the position. In fact, in the CDS market characterized by more buyers than sellers, buyers are those that demand liquidity whereas sellers are those that provide liquidity. As a result, frequent demand-supply imbalances are likely to negatively affect the liquidity in the CDS market and to distort CDS prices. In order to illustrate the effect on CDS prices and to ensure the robustness of the findings, I consider various proxies for demand-supply imbalance (pressure).

$\boldsymbol{BAQ}$ imbalance measure is defined as the difference of the relative proportion of bid and ask quotes in the total number of quotes:

$$BAQ = \frac{NBQ - NAQ}{NQ}$$

Given that the data set consists of one-way and two-way quotes, both are considered for calculating the BAQ measure. The aim of this imbalance measure is to point to the direction of the imbalance, not only to the general imbalance between bid quotes and ask quotes. Acharya et al. (2008) use this measure of imbalance for the bond market but in terms of volume. Given that contracts in the CDS market are quite standardized in terms of nominal value of the reference obligation, this measure should represent a reasonable approximation.

$\boldsymbol{Offerer}$ imbalance measure is defined as the ratio between the number of net ask quotes ($NNAQ$) and the total number of quotes (NQ):

$$Offerer = \frac{NNAQ}{NQ}$$

Acharya et al., (2008) construct $Offerer$ measure for the bond market as the ratio of the net quantity of the offer quote providers on a particular day to the total number of quote providers. As GFI dataset comprises no information on the actual number of quote providers, I proxy supply pressure with the proportion of the number of net ask quotes.

$\boldsymbol{Bidder}$ imbalance measure is constructed to complement the $Offerer$ measure and to proxy for demand pressure. The $Bidder$ measure is defined as the ratio of the number of net bid quotes ($NNBQ$) to the total number of quotes (NQ):

$$Bidder = \frac{NNBQ}{NQ}$$

$\boldsymbol{NBA}$ imbalance measure is defined as the ratio between the number of bid quotes (NBQ) and the number of ask quotes (NAQ):

$$NBA = \frac{NBQ}{NAQ}$$

The NBA proxy for demand-supply imbalance, like the BAQ measure, is designed to indicate whether the imbalance comes from demand or supply side. Meng and Gwilym (2008), as one of the explanatory variables of bid-ask spread, consider the absolute value of one minus the ratio of the number of offers (NAQ) to the number of bids (NBQ) on a given trading day. Such measure proxies for the general demand-supply imbalance, but doesn't reveal its direction, which is the effect analysed in this study. In fact, the demand-supply pressure is not necessarily reflected through the bid-ask spread.

As a control variable for all of the introduced measures, I consider the number of trades to the number of quotes ($T2Q$):

$$T2Q = \frac{NT}{NQ}$$

Actually, $T2Q$ could be considered as liquidity measure that proxies for matching intensity in the CDS market (Tang and Yan, 2007), where a higher matching intensity implies a more speedy trade.

As an additional control variable for BAQ and NBA imbalance measures I introduce the percentage of two-sided quotes ($TSQP$) measure calculated as the ratio between the number of two-sided quotes ($NTSQ$) and the total number of quotes (NQ):

$$TSQP = \frac{NTSQ}{NQ}$$

The $TSQP$ reveals the actual quote balance in the market, and is directly negatively correlated with $Offerer$ and $Bidder$ measures; Therefore, due to the multicolinearity problem these measures cannot be considered jointly.

As regards the effect on the CDS spreads, BAQ, $Bidder$, and NBA imbalance measures are expected to have a positive impact. Namely, at times when sellers are scarce buyers are likely to be willing to bid higher prices, and sellers are likely to ask for a liquidity premium for taking on credit risk in the situation when it becomes more difficult to unwind the taken position. The $Offerer$ measure, in contrast, is expected to have negative impact on CDS spreads. Namely, at good times when investors are readily willing to sell credit protection, sellers are likely to be willing to ask lower prices. The impact on matching intensity, as argued by Tang and Yan (2007) can have different implications on pricing, given that an increasing matching intensity might come either from demand shock or from supply shock. Finally, the $TSQP$ measure is expected to be negatively related with CDS spreads as higher balance of bids and offers implies lower pressure on prices.

Although there is a possibility to refer here to the total number of quotes or number of trades on a given day (NQT), I refrain from this approach for the following reason: higher level of NQT, as a measure of total market activity, could imply higher demand for credit protection, but could also be an indication of the CDS market steady development and maturation reflected through the increase in the number of players in the market. In that sense, for the effect that I want to consider, relative measures seem more appropriate as they have more meaningful and direct interpretation.

Table 3.8 reports the summary of considered imbalance measures and control variables calculated as cross-sectional averages across the European and North American regions for the overall sample period, and for the three distinctive sub-periods. Firm-specific imbalance measures are considered only if both – bid and ask quotes – are available on the same day. Preliminary evidence suggests that the number of bids overpasses the number of offers in all sub-periods and for both regions. During periods of market turbulence, percentage of two-sided quotes is, however, reduced and absolute imbalance is increased, especially within the North American region. It also seems that the measures are of the similar magnitude in both geographical regions.

Table 3.8 *Imbalance measures*

Panel A: Imbalance measures for European companies

Period	BAQ	Offerer	Bidder	NBA	T2Q	TSQP
Period 1	0.020	0.209	0.229	1.101	0.079	0.562
Period 2	0.117	0.108	0.225	1.218	0.074	0.666
Period 3	0.107	0.125	0.231	1.256	0.035	0.644
All	0.094	0.134	0.227	1.201	0.067	0.639

Panel B: Imbalance measures for North American companies

Period	BAQ	Offerer	Bidder	NBA	T2Q	TSQP
Period 1	0.038	0.304	0.342	1.073	0.068	0.355
Period 2	0.055	0.149	0.204	1.076	0.073	0.647
Period 3	0.130	0.193	0.323	1.170	0.091	0.485
All	0.063	0.191	0.254	1.093	0.074	0.555

This table reports different imbalance measures and control variables calculated as cross-sectional averages for the overall sample period, and for three distinctive sub-periods across the European region (Panel A) and the North American region (Panel B).

3.5 Empirical Results

The empirical methodology applied in this chapter is based on extracting the part of the CDS spreads not explained by fundamentals, and relating the non-default component to different imbalance measures. Given that the primary interest of the chapter is on the time variations of the non-default component, there are two additional issues that need to be discussed further: should analysis be conducted on levels or changes, and the time frequency at which the demand-supply imbalance effect is going to be analysed. CDS spreads have unit roots. Running the Augmented Dickey Fuller Test (ADF) for the presence of unit roots shows that firm-specific CDS spreads for 148 out of 163 companies (90.8%) are non-stationary (see Table 3.9). Within the European region, unit roots are detected for 85 out of 92 companies (92.4%) at the 95% confidence level. Likewise, within the North American region, CDS spreads for the majority of the companies are non-stationary - 63 out of 71 (88.7%). Almost the same findings are obtained for firm-specific ICS time-series. On the contrary, the null hypothesis of non-stationarity for the first-differences of CDS spread (and ICS) series is rejected for all companies in the sample.[46] Given that CDS spreads are mostly I(1) processes, running a time-series regression directly on CDS spread levels would give a high R^2, but these regressions are potentially spurious. One of the immediate responses to the non-stationarity of CDS spread series is to consider changes in CDS spreads instead of levels, which is the approach adopted in this chapter and discussed further.

Another important issue refers to the chosen time frequency. By way of example, if changes in $CDSm$ are regressed on contemporaneous changes in ICS_m the R^2 sharply rises from 17% for daily frequency, to 29% for weekly and 51% for monthly frequency for the European region, and from 11%, to 29% and 47% for the North American region. Although

[46] The unit root analysis is also conducted for $CDSm$ and $ICSm$ indexes. Analogous to firm-specific CDS and ICS time-series, $CDSm$ and $ICSm$ indexes are I(1) processes in levels and I(0) processes in differences.

lowering the time frequency at which the data are analyzed has the effect of raising the R^2 statistics, analysis of short-lived liquidity effects asks for higher time frequencies. The majority of the studies on CDS spread determinants use lower time frequencies. For example, Tan and Yang (2007) and Greatrex (2009) use monthly data. This choice of the time frequency is brought by insufficient number of observations on daily basis at the firm-specific level, and possible increased noise in the daily data. For the specific sample of CDSs used in this chapter, bid and ask quotes – and consequently imbalance measures – are available on average every 2.5 days on a firm-specific level.[47] One possibility to overpass these issues is to construct market indices (global market index, and/or rating based indices) as averaging on a cross-sectional basis also has the effect of minimizing the noise in the data while allowing for observations on a daily basis. The other possibility is to use weekly data as in Blanco et al. (2005), and Ericsson et al. (2009). For the aim of robustness both approaches are adopted in this chapter and will be discussed further.

Table 3.9 *Augmented Dickey – Fuller Test (summary results)*

Series	CDSs			ICS		
	Europe	North America	All	Europe	North America	All
Levels						
No. Non-Stationary	85 (92.4%)	63 (88.7%)	148 (90.8%)	81 (88.0%)	61 (85.9%)	142 (87.1%)
No. Stationary	7 (7.6%)	8 (11.3%)	15 (9.2%)	11 (12.0%)	10 (14.1%)	21 (12.9%)
First differences						
No. Non-Stationary	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
No. Stationary	92 (100.0%)	71 (100.0%)	163 (100.0%)	92 (100.0%)	71 (100.0%)	163 (100.0%)

This table provides summary results for the Augmented Dickey-Fuller (ADF) Test for the presence of unit roots in the level of CDS and ICS series, and their first-differences. The table reports the number of companies in the sample for which the test fails to reject the null hypothesis of non-stationarity (unit roots) and the number of companies for which the null hypothesis is rejected. Confidence level of 95% is used as criteria for rejecting the null hypothesis.

[47] Firm-specific imbalance measures are calculated only in the case when both - bid and ask quotes - are present on a given trading day.

3.5.1 CDS innovations

In the vein of the study of Acharya and Johnson (2007), the first step consists of isolating the component of CDS spread changes that is specific solely to credit market, and that is not attributable to changes in fundamentals, that is, CDS innovations. Specifically, CDS innovations are obtained as the residuals from regressing changes in CDS spreads on contemporaneous and lagged changes in fundamentals (ICS), and on lagged changes in CDS spreads as described in the equation (3.2).[48] As such, the residuals of the specified regression could be seen as stock market independent CDS shocks. Lag length is imposed to equal to 5 days, assuming that this is a reasonable time to allow for all information processing and transmission while controlling for the issues of autocorrelation.

$$\Delta CDS_t = \alpha + \sum_{k=0}^{5} \beta_{t-k} \Delta ICS_{t-k} + \sum_{k=1}^{5} \gamma_{t-k} \Delta CDS_{t-k} + e_t. \tag{3.2}$$

Results from the specified regression, conducted using $CDSm$ and $ICSm$ market indexes for the two different regions, and considering three distinctive sub-periods, as well as the overall sample, are presented in Table 3.10. As to the overall period, the adjusted R^2 for the European and North American region amounts to 35.5% and 37.8%, respectively. The adjusted R^2 is substantially higher during periods of credit market turbulence and lower during a quiet period, for both geographical regions. This is in line with common finding in the literature that structural models perform better in explaining the dynamics of CDS spreads during stress times. Moreover, most of the explanatory power can be attributed to contemporaneous and lagged changes in ICSs. This is demonstrated by estimating reduced models in which either: (a) lagged changes in CDS spreads or, (b) contemporaneous and lagged changes in ICSs, are omitted (see Table 3.11).

[48] In the original study Acharya and Johnson (2007) extract CDS innovations on the basis of non-linearly related equity returns, used as a reflection of fundamentals. Instead, I use theoretical credit spreads - ICS.

Table 3.10 *Regression results*

Panel A: Regressions - Europe

Variable	Coefficient	Period 1	Period 2	Period 3	All
ΔICS_t	β_t	0.21 ***	0.18 ***	0.54 ***	0.36 ***
ΔICS_{t-1}	β_{t-1}	0.14 ***	0.10 ***	0.05	0.10 ***
ΔICS_{t-2}	β_{t-2}	0.03	0.01	-0.01	-0.01
ΔICS_{t-3}	β_{t-3}	0.05	-0.01	0.13 *	0.07 **
ΔICS_{t-4}	β_{t-4}	0.01	-0.01	-0.06	0.00
ΔICS_{t-5}	β_{t-5}	0.04	0.01	0.11	0.05 *
ΔCDS_{t-1}	γ_{t-1}	0.27 ***	0.25 ***	0.36 ***	0.33 ***
ΔCDS_{t-2}	γ_{t-2}	0.03	0.10 **	0.01	0.03
ΔCDS_{t-3}	γ_{t-3}	0.11 **	0.03	0.00	0.03
ΔCDS_{t-4}	γ_{t-4}	0.01	0.05	-0.13	-0.09
ΔCDS_{t-5}	γ_{t-5}	-0.01	0.06 *	0.12 **	0.11 ***
adj R^2		0.34	0.21	0.41	0.36
N^0 of observations		369	1001	369	1739

Panel B: Regressions - North America

Variable	Coefficient	Period 1	Period 2	Period 3	All
ΔICS_t	β_t	0.16 ***	0.23 ***	0.13 ***	0.17 ***
ΔICS_{t-1}	β_{t-1}	0.20 ***	0.22 ***	0.22 ***	0.21 ***
ΔICS_{t-2}	β_{t-2}	0.03	0.06	0.14 **	0.05 ***
ΔICS_{t-3}	β_{t-3}	0.05	0.04	0.05	0.04 *
ΔICS_{t-4}	β_{t-4}	0.01	0.02	0.10	0.03
ΔICS_{t-5}	β_{t-5}	-0.01	0.05	0.08	0.02
ΔCDS_{t-1}	γ_{t-1}	0.16 ***	0.12 *	0.02	0.12 ***
ΔCDS_{t-2}	γ_{t-2}	0.14 **	0.01	0.15 **	0.10 ***
ΔCDS_{t-3}	γ_{t-3}	0.11 **	0.09	0.25 ***	0.14 ***
ΔCDS_{t-4}	γ_{t-4}	0.10 *	0.02	0.06	0.06 **
ΔCDS_{t-5}	γ_{t-5}	-0.02	-0.01	-0.10	-0.03
adj R^2		0.39	0.17	0.50	0.38
N^0 of observations		362	1001	351	1714

Table 3.10 presents the results from regressing changes in CDS spreads on contemporaneous and lagged changes in fundamentals (ICS), and lagged changes in CDS spreads. Regressions are conducted using constructed $CDSm$ and $ICSm$ market indexes for the two different regions, and considering three distinctive sub-periods as well as the overall sample. Lag length is imposed to equal 5 days. Standard errors are calculated as Newey-West HAC Standard Errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 3.11 *Regression results*

Panel A: Regressions - Europe

Variable	Coefficient	Period 1		Period 2		Period 3		All	
ΔICS_t	β_t	0.20 ***		0.19 ***		0.54 ***		0.35 ***	
ΔICS_{t-1}	β_{t-1}	0.19 ***		0.15 ***		0.24 ***		0.21 ***	
ΔICS_{t-2}	β_{t-2}	0.08 *		0.07 ***		0.08		0.07 **	
ΔICS_{t-3}	β_{t-3}	0.10 ***		0.05 **		0.16 ***		0.11 ***	
ΔICS_{t-4}	β_{t-4}	0.06 *		0.02		-0.07		0.01	
ΔICS_{t-5}	β_{t-5}	0.08 **		0.05 **		0.12 **		0.08 ***	
ΔCDS_{t-1}	γ_{t-1}		0.38 ***		0.29 ***		0.41 ***		0.40 ***
ΔCDS_{t-2}	γ_{t-2}		0.02		0.11 ***		0.00		0.01
ΔCDS_{t-3}	γ_{t-3}		0.12 **		0.04		0.02		0.04
ΔCDS_{t-4}	γ_{t-4}		0.02		0.02		-0.13		-0.07
ΔCDS_{t-5}	γ_{t-5}		-0.04		0.05		0.17 **		0.11 **
adj R^2		0.27	0.18	0.16	0.14	0.32	0.16	0.26	0.17
N^0 of observations		369	369	1001	1001	369	369	1739	1739

Panel B: Regressions - North America

Variable	Coefficient	Period 1		Period 2		Period 3		All	
ΔICS_t	β_t	0.16 ***		0.23 ***		0.14 **		0.17 ***	
ΔICS_{t-1}	β_{t-1}	0.22 ***		0.25 ***		0.26 ***		0.23 ***	
ΔICS_{t-2}	β_{t-2}	0.09 ***		0.09 ***		0.17 ***		0.10 ***	
ΔICS_{t-3}	β_{t-3}	0.11 ***		0.07 ***		0.09		0.10 ***	
ΔICS_{t-4}	β_{t-4}	0.09 ***		0.06 **		0.20 ***		0.10 ***	
ΔICS_{t-5}	β_{t-5}	0.04		0.07 *		0.15 **		0.06 ***	
ΔCDS_{t-1}	γ_{t-1}		0.32 ***		0.21 ***		0.10		0.23 ***
ΔCDS_{t-2}	γ_{t-2}		0.17 ***		0.04		0.21 ***		0.14 ***
ΔCDS_{t-3}	γ_{t-3}		0.08		0.11		0.30 ***		0.15 ***
ΔCDS_{t-4}	γ_{t-4}		0.05		0.00		0.05		0.03
ΔCDS_{t-5}	γ_{t-5}		-0.04		-0.03		-0.15 *		-0.05 *
adj R^2		0.32	0.22	0.16	0.06	0.37	0.27	0.28	0.14
N^0 of observations		362	362	1001	1001	351	351	1714	1714

Table 3.11 presents results from: (a) regressing changes in CDS spreads on contemporaneous and lagged changes in fundamentals (ICS) and, (b) regressing changes in CDS spreads on lagged changes in CDS spreads. Regressions are conducted using constructed $CDSm$ and $ICSm$ market indexes for the two different regions, and considering three distinctive sub-periods as well as the overall sample. Lag length is imposed to equal to 5 days. Standard errors are calculated as Newey-West HAC Standard Errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

In the second step, extracted daily CDS innovations are related to considered imbalance measures (Imb) within the univariate regression framework described in (3.3a), and within the multivariate regression framework described in (3.3b) that in addition to imbalance measures considers $T2Q$ and $TSQP$ control variables.[49] Imbalance and control measures at market level are calculated as cross-sectional averages at each time point as previously reported in Table 3.8.

$$CDS_{inov,t} = \alpha + \delta_{imb} Imb_t + \varepsilon_t. \tag{3.3a}$$

$$CDS_{inov,t} = \alpha + \delta_{imb} Imb_t + \delta_{t2q} T2Q_t + \delta_{tsqp} TSQP_t + \varepsilon_t. \tag{3.3b}$$

The results, reported in Table 3.12, show that even regressions with daily CDS innovations reveal significance of considered imbalance aspects. As expected, demand pressure has positive effect on CDS innovations. Namely, BAQ, $Bidder$, and NBA measures are positively related to CDS innovations, whereas $Offerer$ measure is negatively related.[50] Interestingly, the $T2Q$ ratio, when significant, is found to have a positive sign, although we would naturally expect a negative sign in all of the cases. One possible explanation could be the result of Acharya and Johnson (2007) who find evidence of informed trading in the most actively traded contracts; and the result of Tang and Yan (2007) who find a positive relation between matching intensity and CDS spreads for contracts with larger probability of informed trading, suggesting that the risk of adverse selection is priced in the CDS market. At last, $TSQP$, when significant, has negative sign as expected, suggesting that a higher

[49] The analysis is robust to employing lagged imbalance measures.
[50] The analysis is also conducted for absolute demand/supply imbalance as described in Meng and Gwilym (2008). The sign of this imbalance measure is not stable suggesting that what matters for CDS pricing is whether the imbalance comes from demand or supply side, not the general imbalance. Given that in the CDS market demand for credit protection more frequently surpasses the supply, in general the impact of the absolute imbalance is found to be positive.

proportion of balanced quotes results in lower CDS innovations.[51] For the overall sample period the demand-supply imbalance has little explanatory power (1% - 3%) across both geographical regions. In terms of economic significance, a one standard deviation increase in BAQ, $Bidder$ and NBA is equivalent, on average, to a 14% standard deviation increase in the CDS innovations for both geographical regions. However, European and North American regions differ substantially across considered sub-periods.[52]

For the European region the explanatory power of the imbalance measures during the first stress period ranges up to 2%, and during the second, quiet period, up to 4%. However, during the recent financial turmoil (Period 3) BAQ, $Bidder$ and NBA measures are able to explain as much as 12%, 14%, and 12%, respectively, of the variations in daily CDS innovations. Although these measures are also significant and with the expected positive sign during the non-crisis period, the absolute value of the coefficients substantially rises in the period of the subprime crisis, suggesting a drastic increase in the economic significance of demand-supply imbalances. Specifically, the magnitude of the coefficients for Period 2 rises: for the BAQ measure from 1.02 to 21.29; for the $Bidder$ measure from 1.38 to 32.09; and for the NBA measure from 0.74 to 9.47. The $Offerer$ measure in Period 3 also has a high magnitude (-20.91), is statistically significant at the 1% level, and explains around 9% of the variations in daily CDS innovations. In terms of economic significance, this means that one standard deviation increase in the demand pressure (BAQ, $Bidder$ and NBA on average) is equivalent to a 36% standard deviation increase in CDS innovations. On the other hand, one standard deviation increase in $Offerer$ is equivalent to a 20% decrease in CDS innovations. The magnitude of the coefficients during the first stress period is also higher compared to the

[51] For the purpose of robustness regressions of CDS innovations on $T2Q$ and $TSQP$ measures are conducted within univariate regression framework as well. The main findings concerning the effect on CDS innovations remain unchanged.

[52] CDS innovations are estimated separately for the three considered sub-periods to allow for eventual structural shifts in CDS-ICS dynamics.

second, quiet period, but still much lower compared to the subprime crisis period. Thus, when making comparison between two stress regimes, it seems that in the second, CDS prices, in addition to default risk, accounted for a high proportion of liquidity risk. These findings are consistent with Acharya et al. (2008). In the "clinical study of Ford and GM downgrade", these authors corroborate that the measures of liquidity have little explanatory power in the quiet non-downgrade period (R^2 of the order of 1% to 3%), but substantial explanatory power during the stress downgrade period.

For the North American region, however, the statistical and economic significance of the considered variables is in general the highest during the first stress period. Specifically, for the first sub-period, BAQ, $Bidde$r and NBA measures can explain around 6%, 7% and 4%, respectively, of the variations in daily CDS innovations, whereas the $Offerer$ measure is able to explain around 3%. In terms of economic significance, one standard deviation increase in the demand pressure (BAQ, $Bidder$ and NBA on average) is equivalent to a 27% standard deviation increase in CDS innovations. In contrast, for the Period 2, magnitude and economic significance of imbalance variables is found to be lower, followed by the explanatory power of up to 4%. Interestingly, I do not find significance for any of the considered variables during the subprime crisis period, and the model even turns out to be misspecified for some of them according to F-statistics. One possible explanation is the drastic decrease in the number of available quote and trade entries during the last sub-period within the available database, and therefore, due to the scarcity of the data the effect could not be analyzed.

Table 3.12 *Regressions on CDS innovations*

Panel A: Regressions - Europe

Period	Variable	BAQ		Offerer		Bidder		NBA	
Period 1	Imb_t	3.02 **	2.92 **	-0.58	-1.14	3.37 *	3.90 **	1.40 **	1.26 *
		(2.54)	*(2.43)*	*(-0.24)*	*(-0.49)*	*(1.90)*	*(2.15)*	*(2.22)*	*(1.73)*
	$T2Q_t$		4.94 **		4.88 *		5.16 **		4.87 **
			(2.03)		*(1.91)*		*(2.06)*		*(1.97)*
	$TSQP_t$		-1.90						-2.21
			(-1.03)						*(-0.77)*
	adj R^2	0.02	0.04	0.00	0.01	0.01	0.03	0.01	0.03
Period 2	Imb_t	1.02 ***	0.76 ***	-0.40	-0.43	1.38 ***	1.36 ***	0.74 ***	0.77 ***
		(4.12)	*(3.12)*	*(-0.55)*	*(-0.57)*	*(3.69)*	*(3.66)*	*(4.46)*	*(3.67)*
	$T2Q_t$		0.22 **		0.35 ***		0.39 ***		0.40 ***
			(2.01)		*(9.52)*		*(11.27)*		*(10.37)*
	$TSQP_t$		-0.66 *						-0.42
			(-1.72)						*(-0.98)*
	adj R^2	0.04	0.05	0.00	0.02	0.03	0.04	0.03	0.06
Period 3	Imb_t	21.29 ***	21.07 ***	-20.91 ***	-20.72 ***	32.09 ***	30.30 ***	9.47 ***	9.69 ***
		(6.07)	*(6.17)*	*(-4.22)*	*(-4.16)*	*(5.82)*	*(5.96)*	*(5.72)*	*(5.68)*
	$T2Q_t$		25.50 **		17.64		26.25 **		13.98
			(2.02)		*(1.29)*		*(2.02)*		*(1.11)*
	$TSQP_t$		-3.47						0.91
			(-0.86)						*(0.22)*
	adj R^2	0.12	0.16	0.09	0.10	0.14	0.15	0.12	0.15
All	Imb_t	3.16 ***	2.95 ***	-1.93 **	-1.80 **	3.51 ***	3.55 ***	1.80 ***	1.81 ***
		(4.70)	*(4.21)*	*(-2.22)*	*(-2.14)*	*(4.99)*	*(4.94)*	*(5.12)*	*(4.77)*
	$T2Q_t$		0.34		0.31 ***		0.37 ***		0.44 ***
			(1.20)		*(2.87)*		*(3.84)*		*(3.46)*
	$TSQP_t$		-0.88 *						-0.32
			(-1.92)						*(-0.69)*
	adj R^2	0.02	0.02	0.01	0.02	0.02	0.02	0.03	0.03

Panel B: Regressions - North America

Period	Variable	BAQ		Offerer		Bidder		NBA	
Period 1	Imb_t	2.96 ***	3.09 ***	-3.76 ***	-3.76 ***	5.98 ***	6.08 ***	1.33 ***	1.66 ***
		(4.84)	*(5.18)*	*(-3.59)*	*(-3.54)*	*(5.33)*	*(5.45)*	*(3.48)*	*(4.26)*
	$T2Q_t$		-1.39		-0.47		-1.46		-1.99
			(-0.91)		*(-0.21)*		*(-1.00)*		*(-1.28)*
	$TSQP_t$		-2.78 **						-3.88 ***
			(-2.42)						*(-3.23)*
	adj R^2	0.06	0.07	0.03	0.03	0.07	0.07	0.04	0.06
Period 2	Imb_t	2.04 ***	2.03 ***	-2.62 ***	-2.81 ***	2.49 ***	2.63 ***	1.11 ***	1.11 ***
		(5.92)	*(5.68)*	*(-4.22)*	*(-4.90)*	*(5.66)*	*(5.69)*	*(5.61)*	*(5.55)*
	$T2Q_t$		-0.01		0.24		0.01		0.14
			(-0.06)		*(1.35)*		*(0.05)*		*(1.03)*
	$TSQP_t$		-0.18						-0.60 *
			(-0.55)						*(-1.84)*
	adj R^2	0.04	0.04	0.02	0.02	0.03	0.03	0.03	0.03
Period 3	Imb_t	1.19	1.31	-2.21	-2.30	1.19	1.23	1.95	2.03
		(1.15)	*(1.28)*	*(-1.36)*	*(-1.40)*	*(0.82)*	*(0.82)*	*(1.62)*	*(1.56)*
	$T2Q_t$		0.05		0.10		-0.12		-0.07
			(0.10)		*(0.21)*		*(-0.25)*		*(-0.21)*
	$TSQP_t$		-0.67						-1.06
			(-0.66)						*(-0.65)*
	adj R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02
All	Imb_t	2.13 ***	2.15 ***	-2.68 ***	-2.82 ***	2.39 ***	2.42 **	1.83 ***	1.87 ***
		(2.98)	*(3.06)*	*(-2.93)*	*(-3.13)*	*(2.60)*	*(2.46)*	*(2.73)*	*(2.78)*
	$T2Q_t$		0.09		0.28		-0.07		0.14
			(0.35)		*(1.26)*		*(-0.27)*		*(0.69)*
	$TSQP_t$		-0.14						-0.71 *
			(-0.29)						*(-1.68)*
	adj R^2	0.02	0.02	0.01	0.01	0.01	0.01	0.03	0.03

Table 3.12 reports results obtained from regressing CDS innovations on different imbalance measures (BAQ, $Offerer$, $Bidder$, NBA), and control variables ($T2Q$, and $TSQP$). Regressions are estimated for the aggregate European (Panel A) and North American (Panel B) market level using daily frequency. Standard errors are calculated as Newey-West HAC Standard Errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 3.13 *Regressions on CDS innovations for investment and non-investment grade sub-samples*

Panel A: Regressions - investment grade European companies

Period	Variable	BAQ		Offerer		Bidder		NBA	
All	Imb_t	2.23 ***	2.27 ***	-1.72 ***	-1.81 ***	1.93 ***	1.93 ***	1.18 ***	1.28 ***
		(4.78)	*(4.63)*	*(-3.24)*	*(-3.33)*	*(4.76)*	*(4.76)*	*(5.22)*	*(5.09)*
	$T2Q_t$		0.52		0.16		0.20 **		0.24 **
			(0.94)		*(1.54)*		*(2.34)*		*(2.13)*
	$TSQP_t$		-0.16						-0.31
			(-0.59)						*(-1.31)*
	adj R^2	0.01	0.01	0.00	0.00	0.01	0.01	0.02	0.02

Panel B: Regressions - non-investment grade European companies

Period	Variable	BAQ		Offerer		Bidder		NBA	
All	Imb_t	2.59 **	2.43 **	-1.07	-1.15	4.53 ***	4.54 ***	1.47 ***	1.45 ***
		(2.57)	*(2.34)*	*(-0.66)*	*(-0.70)*	*(3.37)*	*(3.37)*	*(3.11)*	*(2.77)*
	$T2Q_t$		0.48		0.47		0.43		0.40
			(0.45)		*(0.44)*		*(0.42)*		*(0.65)*
	$TSQP_t$		-2.06 *						-2.07 *
			(-1.88)						*(-1.89)*
	adj R^2	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01

Panel C: Regressions - investment grade North American companies

Period	Variable	BAQ		Offerer		Bidder		NBA	
All	Imb_t	0.73 ***	0.74 ***	-1.00 ***	-1.02 ***	0.87 ***	0.87 ***	0.51 ***	0.51 ***
		(4.35)	*(4.31)*	*(-3.81)*	*(-3.84)*	*(4.05)*	*(4.04)*	*(4.23)*	*(4.23)*
	$T2Q_t$		0.04		0.07		0.01		0.04
			(0.75)		*(1.52)*		*(0.26)*		*(0.77)*
	$TSQP_t$		-0.05						-0.09
			(-0.36)						*(-0.54)*
	adj R^2	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02

Panel D: Regressions - non-investment grade North American companies

Period	Variable	BAQ		Offerer		Bidder		NBA	
All	Imb_t	1.80 ***	1.72 ***	-1.88 **	-1.90 **	2.57 ***	2.59 ***	1.15 **	1.19 **
		(3.73)	*(3.65)*	*(-2.52)*	*(-2.52)*	*(3.32)*	*(3.34)*	*(2.18)*	*(2.19)*
	$T2Q_t$		0.10		0.23		0.08		0.29
			(0.61)		*(0.58)*		*(0.21)*		*(0.42)*
	$TSQP_t$		-0.85						-1.24 *
			(-1.26)						*(-1.83)*
	adj R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 3.13 reports results obtained from regressing CDS innovations on different imbalance measures (BAQ, $Offerer$, $Bidder$, NBA), and control variables ($T2Q$, and $TSQP$). Regressions are estimated for the investment and non-investment grade subsamples for European (Panel A and Panel B) and North American (Panel C and Panel D) regions using daily frequency. Standard errors are calculated as Newey-West HAC Standard Errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

For the purpose of robustness, I repeat the analysis for constructed investment and non-investment grade indices across the two regions. Results for the overall sample period are illustrated in Table 3.13. Essentially, the main findings from regressing CDS innovations on imbalance and control measures in terms of sign and significance of the coefficients remain the same across the two different rating classes. Nevertheless, the magnitude of the coefficients seems to be higher for the non-investment grade class, especially for the North American region. On the other hand, the explanatory power is somewhat lower for the non-investment class compared to the investment grade class.

The previous analysis has been done on the basis of daily CDS innovations. Acharya at al. (2008), however, aggregate residuals on a weekly basis to suppress the noise in the data and conduct analysis further on weekly basis. If I take the same approach and further aggregate the obtained daily innovations to weekly CDS innovations, the explanatory power of the imbalance measures in general rises on an aggregate market level. However, for robustness purposes, I extend the previous analysis by running firm-specific time-series regressions on a weekly basis to obtain firm-specific weekly residuals. For that purpose I consider a model in which changes in CDS spreads are regressed on contemporaneous and one lag changes in ICSs and one lag changes in CDS spreads:

$$\Delta CDS_t = \alpha + \sum_{k=0}^{1} \beta_{t-k} \Delta ICS_{t-k} + \gamma_{t-1} \Delta CDS_{t-1} + e_t. \tag{3.4}$$

Further I run univariate and multivariate time-series regression of CDS innovations on different imbalance and control variables of the form described in (3.3a) and (3.3b). Given that the dataset now turns into a pooled time-series and cross-section unbalanced panel in which both firm and time effects are present, standard errors must be corrected for possible dependence in residuals. Following Petersen (2009) the firm effect is controlled for in a parametric form by including firm dummies, whereas the time effect is eliminated using clustered by time period standard errors.[53] To avoid the eventual effect of outsiders, firm-specific weekly observations are included only if both bid and ask quotes are available. The coefficients and corresponding t-statistics for the overall sample period and the two geographical regions are depicted in Table 3.14. Results are consistent with previous findings on an aggregate market level.

Table 3.14 *Regression results*

Panel A: Regressions - Europe

Variable	Coefficient	BAQ		Offerer		Bidder		NBA	
Imb_t	$\delta_{imb,t}$	2.58 ***	2.69 ***	-4.30 ***	-4.30 ***	6.40 ***	6.44 ***	1.60 ***	1.68 ***
		(4.21)	*(4.97)*	*(-3.23)*	*(-3.23)*	*(5.82)*	*(5.86)*	*(5.40)*	*(5.34)*
$T2Q_t$	$\delta_{t2q,t}$		0.61		0.52		0.63		0.69
			(0.63)		*(1.32)*		*(1.57)*		*(0.78)*
$TSQP_t$	$\delta_{tsqp,t}$		-2.07 **						-1.42
			(-2.04)						*(-1.40)*
adj R^2		0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01

Panel B: Regressions - North America

Variable	Coefficient	BAQ		Offerer		Bidder		NBA	
Imb_t	$\delta_{imb,t}$	2.74 ***	2.69 ***	-3.46 ***	-3.46 ***	4.02 ***	3.93 ***	1.87 ***	1.86 ***
		(7.47)	*(7.54)*	*(-6.57)*	*(-6.56)*	*(5.17)*	*(5.17)*	*(4.90)*	*(4.83)*
$T2Q_t$	$\delta_{t2q,t}$		1.36		1.63		1.29		2.05
			(1.10)		*(1.29)*		*(1.04)*		*(1.22)*
$TSQP_t$	$\delta_{tsqp,t}$		-0.44						-0.65
			(-0.64)						*(-0.78)*
adj R^2		0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01

Table 3.14 shows the coefficients and corresponding t-statistics from regressing firm-specific CDS innovations on different imbalance measures (BAQ, $Offerer$, $Bidder$, NBA), and control variables ($TSQP$ and $T2Q$). Standard errors are clustered by time and firm dummies are included to control for the firm effect. Regressions are estimated using weekly frequency. Weekly firm-specific CDS innovations are obtained by regressing changes in CDS spreads on contemporaneous and one lag changes in ICSs, and one lag changes in CDS spreads. Number of observations is: 25,268 for European region and 15,678 for North American region. *** indicates

[53] Standard errors clustered by time are higher than White standard errors and somewhat higher than standard errors clustered by firm.

significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Another interesting issue to consider is: up to what extent firm-specific CDS innovations are influenced by aggregate, market demand-supply imbalance. To investigate this question, I have run a regression in which firm-specific CDS innovations are regressed on firm-specific imbalance measures (Imb_i) and aggregate market imbalance (Imb_m).

$$CDS_{inov,t} = \alpha + \delta_i Imb_{i,t} + \delta_m Imb_{m,t} + \varepsilon_t. \quad (3.5)$$

The results, shown in Table 3.15, reveal that firm-specific CDS innovations are largely affected by aggregate market imbalance. This finding could be related with funding constraints of sellers in the CDS market.

Table 3.15 *Regression results*

Panel A: Regressions - Europe

Variable	Coefficient	BAQ	Offerer	Bidder	NBA
$Imb_{i,t}$	$\delta_{i,t}$	1.77 ***	-4.80 ***	4.49 ***	1.24 ***
		(3.54)	*(-4.43)*	*(4.95)*	*(4.52)*
$Imb_{m,t}$	$\delta_{m,t}$	11.35 ***	-3.99	8.95 ***	1.46 ***
		(3.75)	*(-0.42)*	*(2.82)*	*(3.77)*
adj R^2		0.01	0.00	0.01	0.01

Panel A: Regressions - Europe

Variable	Coefficient	BAQ	Offerer	Bidder	NBA
$Imb_{i,t}$	$\delta_{i,t}$	1.31 ***	-1.83 ***	1.92 ***	1.51 ***
		(3.38)	*(-3.78)*	*(3.03)*	*(4.66)*
$Imb_{m,t}$	$\delta_{m,t}$	17.96 ***	-13.83 **	16.60 ***	4.35 ***
		(5.82)	*(-3.44)*	*(4.12)*	*(5.08)*
adj R^2		0.02	0.01	0.01	0.02

Table 3.15 shows the coefficients and corresponding t-statistics from regressing firm-specific CDS innovations on different firm-specific (Imb_i) and market-wide (Imb_m) imbalance measures (BAQ, $Offerer$, $Bidder$, NBA). Standard errors are clustered by time, and firm dummies are included to control for the firm effect. Regressions are estimated using weekly frequency. Weekly firm-specific CDS innovations are obtained by regressing changes in CDS spreads on contemporaneous and one lag changes in ICSs, and one lag changes in CDS spreads. Number of observations is: 25,268 for European region and 15,678 for North American region. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

3.5.2 Robustness checks

To ensure the robustness of the presented findings several additional analyses are conducted. First, I consider a model in which changes in CDS spreads are regressed on contemporaneous and lagged changes in fundamentals (ICS), lagged changes in CDS spreads, and contemporaneous and lagged changes in different imbalance measures (Imb). Namely, I consider the following model:

$$\Delta CDS_t = \alpha + \sum_{k=0}^{5} \beta_{t-k} \Delta ICS_{t-k} + \sum_{k=1}^{5} \gamma_{t-k} \Delta CDS_{t-k} + \sum_{k=0}^{5} \delta_{imb,t-k} \Delta Imb_{t-k} + e_t, \quad (3.6)$$

as well as its extension with the $T2Q$ and $TSQP$ control variables. Results from the regressions estimated using daily frequency on aggregate market level (i.e. using $CDSm$ and $ICSm$ indices) for the overall period across the European and North American regions are reported in Table 3.16. The signs of the significant coefficients are consistent with previous findings. The increase in the demand pressure proxied by positive changes in BAQ, $Bidde$r, and NBA measures, is positively related with changes in CDS spreads. In contrast, increased supply proxied by positive changes in the $Offerer$ measure is negatively related with changes in CDS spreads.

Table 3.16 *Regression results*

Panel A: Regressions - Europe

Variable	Coefficient	BAQ		Offerer		Bidder		NBA	
$\Delta ICS_{t-k,\, k=0,\ldots,5}$	$\Sigma\beta_{t-k}$	0.56 ***	0.56 ***	0.58 ***	0.58 ***	0.55 ***	0.55 ***	0.54 ***	0.54 ***
		(6.80)	*(6.74)*	*(7.03)*	*(7.03)*	*(6.73)*	*(6.74)*	*(6.70)*	*(6.65)*
$\Delta CDS_{t-k,\, k=1,\ldots,5}$	$\Sigma\gamma_{t-k}$	0.41 ***	0.42 ***	0.41 ***	0.41 ***	0.41 ***	0.42 ***	0.42 ***	0.42 ***
		(5.39)	*(5.38)*	*(5.23)*	*(5.23)*	*(5.35)*	*(5.35)*	*(5.44)*	*(5.44)*
$\Delta Imb_{t-k,\, k=0,\ldots,5}$	$\Sigma\delta_{imb,t-k}$	15.31 ***	14.50 ***	-20.34 ***	-19.65 ***	22.01 ***	21.49 ***	7.94 ***	7.97 ***
		(3.64)	*(3.36)*	*(-3.21)*	*(-3.13)*	*(3.50)*	*(3.41)*	*(4.03)*	*(3.73)*
$\Delta T2Q_{t-k,\, k=0,\ldots,5}$	$\Sigma\delta_{t2q,t-k}$		-5.77		-4.97		-7.15		-4.95
			(-0.95)		*(-0.82)*		*(-1.23)*		*(-0.78)*
$\Delta TSQP_{t-k,\, k=0,\ldots,5}$	$\Sigma\delta_{tsqp,t-k}$		-2.18						-0.37
			(-0.59)						*(-0.10)*
adj R^2		0.37	0.37	0.36	0.36	0.37	0.37	0.37	0.36

Panel B: Regressions - North America

Variable	Coefficient	BAQ		Offerer		Bidder		NBA	
$\Delta ICS_{t-k,\, k=0,\ldots,5}$	$\Sigma\beta_{t-k}$	0.49 ***	0.48 ***	0.50 ***	0.50 ***	0.49 ***	0.49 ***	0.50 ***	0.49 ***
		(8.73)	*(8.64)*	*(8.97)*	*(8.89)*	*(8.68)*	*(8.64)*	*(9.09)*	*(8.98)*
$\Delta CDS_{t-k,\, k=1,\ldots,5}$	$\Sigma\gamma_{t-k}$	0.42 ***	0.42 ***	0.42 ***	0.42 ***	0.41 ***	0.41 ***	0.42 ***	0.42 ***
		(7.85)	*(7.83)*	*(7.87)*	*(7.86)*	*(7.65)*	*(7.62)*	*(7.92)*	*(7.88)*
$\Delta Imb_{t-k,\, k=0,\ldots,5}$	$\Sigma\delta_{imb,t-k}$	6.24 ***	6.21 ***	-8.30 ***	-8.84 ***	9.75 ***	9.80 ***	4.00 ***	4.19 ***
		(4.62)	*(4.60)*	*(-3.67)*	*(-3.91)*	*(4.35)*	*(4.33)*	*(3.95)*	*(4.06)*
$\Delta T2Q_{t-k,\, k=0,\ldots,5}$	$\Sigma\delta_{t2q,t-k}$		1.46		2.72		0.35		0.83
			(0.73)		*(1.41)*		*(0.19)*		*(0.44)*
$\Delta TSQP_{t-k,\, k=0,\ldots,5}$	$\Sigma\delta_{tsqp,t-k}$		-1.09						-2.74
			(-0.53)						*(-1.28)*
adj R^2		0.40	0.40	0.39	0.39	0.39	0.39	0.39	0.39

Table 3.16 reports results obtained from regressing changes in CDS spreads on contemporaneous and lagged changes in fundamentals (ICS), lagged changes in CDS spreads, contemporaneous and lagged changes in different imbalance measures (BAQ, $Offerer$, $Bidder$, NBA), and contemporaneous and lagged changes in control variables ($T2Q$, and $TSQP$). Regressions are estimated using daily frequency on aggregate market level (i.e. using $CDSm$ and $ICSm$ indices) for the overall period across the European (Panel A) and North American (Panel B) regions. Number of observations is: 1,739 for European region and 1,714 for North American region. Standard errors are calculated as Newey-West HAC Standard Errors. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

The other valid approach would be to consider deviations from long-run equilibrium relationship between CDS and ICS series. If we depart from the idea that CDS spreads and ICSs price credit risk equally in the long run, then we can apply the cointegration approach and explore the transitory movements in CDS spreads. Given that CDS spread series are integrated of order 1 (denoted I(1)), innovations in CDS spreads contain at least one permanent component which should be directly associated with permanent changes in fundamentals. If there exists a linear combination of CDS spreads and ICSs that is stationary (denoted I(0)), then there exists a time-varying long-run equilibrium between employed variables. Furthermore, if changes in ICS spreads are only the reflection of permanent changes in fundamentals, then transitory changes in CDS spreads (CDS innovations) would correspond to changes in cointegrating residuals.

The presence of cointegration is tested on the basis of the econometric methodology developed by Johansen and Juselius (1990) and Johansen (1996). If variables are cointegrated then they allow the VECM representation, defined shortly as:

$$\Delta Y_t = \mu_0 + \alpha\beta' Y_{t-1} + \sum_{i=1}^{\infty} \Gamma_{\mathrm{i}} \Delta Y_{t-i} + \varepsilon_t \tag{3.7}$$

where Y_t is a 2x1 vector of I(1) time series ($Y_t^{'} = [CDS_t; ICS_t]$), $\Delta = 1 - L$ is the lag operator, Π and Γ_{i} are pxp matrices of coefficients, and μ_0 is a constant. The specification that is estimated allows a separate drift in VAR and a non-zero mean for the cointegrating relation. Summary of the results of the Johansen based cointegration test are presented in Table 3.17. I have found significant cointegrating relationships for 93 companies (57.1% of the sample) at the 5% significance level and for 107 companies (65.6% of the sample) at the 10% significance level. The number of companies with a CDS-ICS cointegrating relationship is quite balanced between the two examined regions. A significant cointegration relationship for the majority of the examined companies further implies that structural models are able to price credit risk in the long-run.

Table 3.17 *Johansen Cointegration Test (Summary results)*

Series	Johansen Cointegration Test		
	Europe	North America	All
At 5%			
Cointegration	50 (54.3%)	43 (60.6%)	93 (57.1%)
No cointegration	42 (45.7%)	28 (39.4%)	70 (42.9%)
At 10%			
Cointegration	59 (64.1%)	48 (67.6%)	107 (65.6%)
No cointegration	33 (35.9%)	23 (32.4%)	56 (34.4%)

This table provides summary results for the Johansen Cointegration Tests for the pairs of ICS – CDS spread series. A constant is allowed both in the cointegration equation and in the VAR component of the VECM, whereas the number of lags is determined according to the Schwarz Information Criterion. The table reports the number of companies in the sample for which the cointegration is detected and the number of companies for which it is rejected at the 5% and 10% significance level.

For the sub-sample of companies with significant cointegrating relationship at the 10% level, CDS innovations streaming from the cointegrating residuals are first aggregated to weekly levels and then related to different imbalance measures (Imb). In this way I deal only with short-run movements in CDS spreads that are not explained by firm-specific fundamentals.[54] The regression framework is summarized in equation (3.8). It contains contemporaneous and one-period lagged imbalance measures, as well as one-period lagged dependent variable as the cointegrating residuals seem to be quite persistent. Also, the specified model is extended to account for the corresponding control variables.

[54] There is also the option to decompose ICSs into its permanent and transitory (PT) component and to consider the PT decomposition of Gonzalo and Granger (1995). Strictly speaking, under the PT decomposition, the hypothesis made in this paper is the same as assuming that the CDS market is the only market that adjusts to the long-run equilibrium. This is not such an unreasonable assumption given that the major part of credit risk discovery occurs in fact in the stock market. Gonzalo and Granger's (GG) contributions of stock market to the common factor are 0.62 for the European and 0.64 for the North American region on average (if contributions higher than 1 and lower than 0 are not set to 1 and 0 respectively, then contributions are much higher: 0.84 and 0.74). Moreover, within the European region, for 29 companies (50%) I fail to reject null hypothesis α=0 at the 5% level and for 44 (75%) at the 1% level. Within the North American region, for 24 companies (50%) I fail to reject null hypothesis α=0 at the 5% level and for 37 (77%) at the 1% level. This means that for these companies the common factor for the two series reduces to the fundamental ICS series.

$$CDS_{inov,t} = \alpha + \sum_{k=0}^{1} \delta_{imb,k}\, Imb_{t-k} + \eta_{t-1} CDS_{inov,t-1} + \varepsilon_t. \tag{3.8}$$

Detailed results for the overall sample period and for both the European and North American regions, are depicted in Table 3.18. To save space, only the results from the reduced model (i.e. without controls) are presented in Table 3.19 where the overall sample is divided into three sub-periods. The reported slopes and t-statistics (in parentheses), are computed using firm dummies and clustering by time. Results are consistent with previous findings and indicate that imbalance measures significantly influence short-run CDS transitory movements in the expected direction. Another important and expected finding is that the magnitude of the coefficients is in general larger for the sub-periods of credit distress (Period 1 and Period 3), implying higher economic significance of imbalance measures during bad times. Also, the positive impact of the $T2Q$ ratio is confirmed, what is consistent with the hypothesis of insider trading in credit derivatives. Finally, it seems that coefficients are in general larger for the European sub-sample, implying higher economic impact across this region.

Table 3.18 *Regression results - cointegrating residuals*

Panel A: Regressions - Europe

Variable	Coefficient	BAQ		Offerer		Bidder		NBA	
Imb_t	$\delta_{imb,t}$	2.08 ***	2.07 ***	-4.26 ***	-4.27 ***	6.43 ***	6.47 ***	1.60 ***	1.67 ***
		(3.24)	*(3.34)*	*(-3.35)*	*(-3.36)*	*(4.91)*	*(4.94)*	*(5.09)*	*(4.90)*
Imb_{t-1}	$\delta_{imb,t-1}$	2.55 ***	2.85 ***	-1.25	-1.27	3.18 ***	3.18 ***	1.80 ***	1.84 ***
		(3.39)	*(3.86)*	*(-0.93)*	*(-0.95)*	*(2.77)*	*(2.77)*	*(4.85)*	*(4.90)*
$T2Q_t$	$\delta_{t2q,t}$		0.36		0.53		0.62		0.56
			(0.53)		*(1.38)*		*(1.53)*		*(0.34)*
$T2Q_{t-1}$	$\delta_{t2q,t-1}$		-0.18		0.33		0.35		-0.25
			(-0.14)		*(0.59)*		*(0.64)*		*(-0.13)*
$TSQP_t$	$\delta_{tsqp,t}$		-2.26 *						-1.66
			(-1.93)						*(-1.44)*
$TSQP_{t-1}$	$\delta_{tsqp,t-1}$		-0.74						-0.16
			(-0.67)						*(-0.15)*
$CDS_{inov,t-1}$	η_{t-1}	0.16 ***	0.16 ***	0.17 ***	0.17 ***	0.17 ***	0.17 ***	0.15 ***	0.16 ***
		(3.21)	*(3.20)*	*(3.28)*	*(3.28)*	*(3.23)*	*(3.22)*	*(3.21)*	*(3.20)*
	adj R^2	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.03

Panel B: Regressions - North America

Variable	Coefficient	BAQ		Offerer		Bidder		NBA	
Imb_t	$\delta_{imb,t}$	1.64 ***	1.63 ***	-1.89 **	-1.90 ***	2.30 **	2.24 **	1.19 ***	1.14 ***
		(3.38)	*(3.39)*	*(-2.59)*	*(-2.59)*	*(2.32)*	*(2.28)*	*(3.59)*	*(3.40)*
Imb_{t-1}	$\delta_{imb,t-1}$	3.35 ***	3.31 ***	-3.87 ***	-3.89 ***	5.09 ***	5.07 ***	1.79 ***	1.80 ***
		(5.80)	*(5.79)*	*(-4.41)*	*(-4.45)*	*(4.74)*	*(4.74)*	*(3.54)*	*(3.55)*
$T2Q_t$	$\delta_{t2q,t}$		3.33 *		3.60 *		3.19 *		4.18 ***
			(1.75)		*(1.88)*		*(1.68)*		*(2.73)*
$T2Q_{t-1}$	$\delta_{t2q,t-1}$		0.39		0.82		0.32		1.36
			(0.19)		*(0.39)*		*(0.15)*		*(0.67)*
$TSQP_t$	$\delta_{tsqp,t}$		-0.19						-0.99
			(-0.21)						*(-1.02)*
$TSQP_{t-1}$	$\delta_{tsqp,t-1}$		-1.00						0.43
			(-1.11)						*(0.45)*
$CDS_{inov,t-1}$	η_{t-1}	0.12 ***	0.11 ***	0.12 ***	0.12 ***	0.12 ***	0.12 ***	0.11 ***	0.11 ***
		(3.28)	*(3.28)*	*(3.33)*	*(3.33)*	*(3.29)*	*(3.29)*	*(3.09)*	*(3.04)*
	adj R^2	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02

Table 3.18 reports the results of the regression of changes in cointegrating residuals as CDS innovations on contemporaneous and one-period lagged imbalance measures (BAQ, $Offerer$, $Bidder$, NBA), (with or without) control variables ($TSQP$ and $T2Q$), and one lag of the dependent variable. Regressions are estimated using weekly frequency. Number of observations is: 16,955 for European region and 10,649 for North American region. The reported slopes and t-statistics (in parentheses), are computed using firm dummies and clustering by

time. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 3.19 *Regression results - cointegrating residuals*

Panel A: Regressions - Europe (per period)						**Panel B:** Regressions - North America (per period)					
Period	Coefficient	BAQ	Offerer	Bidder	NBA	Period	Coefficient	BAQ	Offerer	Bidder	NBA
Period 1	$\delta_{imb,t}$	4.98 ***	-7.39 **	7.07 **	3.13 ***	Period 1	$\delta_{imb,t}$	1.92 **	-2.38 *	4.46 ***	1.61 **
		(3.79)	*(-2.57)*	*(2.31)*	*(3.25)*			*(2.33)*	*(-1.67)*	*(2.74)*	*(2.62)*
	$\delta_{imb,t-1}$	2.85 **	-1.06	1.65	2.51 ***		$\delta_{imb,t-1}$	5.60 ***	-9.28 ***	9.77 ***	3.40 ***
		(2.56)	*(-0.47)*	*(0.53)*	*(2.80)*			*(5.56)*	*(-5.66)*	*(4.64)*	*(3.55)*
	adj R^2	0.01	0.01	0.01	0.01		*adj* R^2	0.02	0.01	0.02	0.02
Period 2	$\delta_{imb,t}$	1.15 ***	-0.62	2.14 *	0.65 ***	Period 2	$\delta_{imb,t}$	1.63 ***	-2.22 ***	2.10 ***	0.86 ***
		(2.97)	*(-0.45)*	*(1.96)*	*(3.24)*			*(3.55)*	*(-3.38)*	*(2.84)*	*(3.38)*
	$\delta_{imb,t-1}$	1.15 ***	0.33	3.22 ***	0.75 ***		$\delta_{imb,t-1}$	2.48 ***	-2.39 ***	4.01 ***	0.89 ***
		(3.03)	*(0.23)*	*(2.65)*	*(3.15)*			*(4.86)*	*(-2.81)*	*(5.65)*	*(3.98)*
	adj R^2	0.02	0.02	0.02	0.03		*adj* R^2	0.02	0.01	0.01	0.01
Period 3	$\delta_{imb,t}$	1.82	-7.89 **	13.73 ***	3.01 ***	Period 3	$\delta_{imb,t}$	1.20	0.14	2.89	1.59
		(0.89)	*(-2.39)*	*(3.76)*	*(4.03)*			*(0.55)*	*(0.04)*	*(0.69)*	*(0.85)*
	$\delta_{imb,t-1}$	6.57 **	-6.69 **	8.88 ***	4.15 ***		$\delta_{imb,t-1}$	0.70	3.28	4.09	1.40
		(2.30)	*(-2.63)*	*(2.85)*	*(3.99)*			*(0.22)*	*(0.59)*	*(0.89)*	*(0.75)*
	adj R^2	0.04	0.03	0.04	0.04		*adj* R^2	0.00	0.00	0.00	0.00

Table 3.19 reports the results of the regression of changes in cointegrating residuals as CDS innovations on contemporaneous and one-period lagged imbalance measures (BAQ $Offerer$, $Bidder$, NBA), and one lag of the dependent variable. Regressions are estimated using weekly frequency. The reported slopes and t-statistics (in parentheses), are computed using firm dummies and clustering by time. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Finally, in order to insure the robustness of the results to the way in which daily CDS spread observations are constructed, all the analyses conducted in this study are repeated for several alternative ways of constructing daily CDS spread observations. The first alternative follows the algorithm: if on a given day both bid and ask quotes are present, then CDS spread refers to the midpoint of the average bid and average ask quotes; if only the bid (ask) quotes are available on a particular day, then the ask (bid) is computed assuming that the relative bid-ask spread is equal to the one on the previous most recent day. The second possibility refers only to using two-sided quotes when calculating CDS spread observations. The third possibility consists of using only realized transaction entries as a reference CDS spread observations. Main findings of the study are not materially affected by these different specifications.

3.6 Conclusions

The recent financial crisis has put doubt on considering CDS spreads as a “pure” measure of credit risk by revealing their clear sensitivity to liquidity shocks. To shed light upon this issue in this chapter I empirically examine the effect of structural demand-supply imbalances on changes in CDS spreads that cannot be attributed to fundamentals. Theoretical determinants of credit risk are jointly accounted for by means of theoretical stock market implied credit spreads derived on the basis of a structural credit risk model. Data set consists of a large and homogenous international sample of 163 non-financial companies (92 European and 71 North American) with relatively active quotes during the time period spanning from 2002-2008.

The results indicate that short-term CDS price movements, not related to fundamentals, are indeed affected by bid and offer imbalance, especially in stress times. An increase in the number of buyers as regards sellers, corroborated on the basis of different imbalance measures, has an increasing effect on CDS prices. This indicates that CDS spreads reflect not only the price of credit protection, but also a premium charged by protection seller in situations when it becomes more difficult to offset the taken position. The effect is particularly visible within European region during the recent subprime crisis period. The results also indicate that matching intensity is positively related with CDS spreads, what is consistent with the hypothesis of information asymmetry and insider trading within CDS market.

Conclusions and Further Research

This thesis treats the estimation and applications of theoretically attractive structural credit risk models in the specific context of assessing and analysing the information on credit risk embodied in the stock market and market for credit derivatives (CDS market). It is built on the idea that, under the structural model framework, information on credit risk can be extracted from information on stock prices. Following this basic setting three issues are analysed: the relative informational content of stock and CDS market as regards credit risk, the problem of estimation of latent model parameters and, finally, the existence of non-default liquidity components in CDS spreads. The overall research presented in this study leads to the sets of conclusions, from theoretical and empirical point of view.

First, the study contributes to the existing debate on the performance of structural credit risk models by demonstrating in several ways that these models are indeed useful for credit risk pricing. Namely, it shows that CDS spreads observed in the market can be replicated quite well by its theoretical counterparts as long as the appropriate procedure is applied when estimating the model parameters. A new procedure, that outperforms other options available for structural models with exogenously specified default barrier, has been proposed. In addition, the analyses made in the thesis show that theoretical - stock market implied credit spreads based on structural models, can explain substantial part of the cross-sectional variation of the CDS spread levels. The empirical findings also suggest that explanatory power of structural models when explaining changes in CDS spreads sharply increases during stress periods. Finally, when considering a large time-period for CDS market (2002-2008), it seems that theoretical parity relationship between stock and CDS market holds as an equilibrium condition for the majority of the cases, implying that these markets do price credit risk equally in the long-run.

Second set of conclusions refers to the short-run context of the relative informational content of stock market implied credit spreads and CDS spreads - directly comparable indicators of the price of credit risk in two different markets (stock and CDS market). The analysis documents time-varying relative informational content of two alternative proxies for the same latent variable – “pure” credit spread. Likewise, the analysis suggests that leading role of stock market as the source of information as regards credit risk increases with the overall credit risk level. This result, however, is not inconsistent with the argument of insider trading in credit derivatives; a positive relationship between the frequency of severe credit downturns and the probability of the CDS market leading credit risk discovery is documented.

Third set of findings is related to the context of the presence of non-default components in CDS spreads traditionally believed to be “pure” measures of credit risk. To shed light upon this issue, the effect of demand-supply imbalances on the changes in CDS spreads not accounted by fundamentals (ICS) is analyzed. It is shown that this aspect of liquidity in the CDS market has important consequences on CDS prices. Namely, it is demonstrated that an increase in the number of buyers as regards sellers has an increasing effect on CDS prices, and that the protection seller will charge a premium in situations when it becomes more difficult to offset the taken position. These findings have direct implication for using CDS spreads as a market benchmark when testing the performance of structural models. The underperformance of ICSs may not be due to underestimation of credit risk per se, but due to the fact that CDS spreads contain non-default components.

The findings of the study together with the proposed estimation procedure set the background for different empirical applications. One possible application lies on the fact that the default barrier, along with the value, volatility, and expected return on the firm's assets, are estimated from stock market exclusively. This means that estimation of model parameters referred above is possible even in the cases when the information from CDS market is unavailable or unreliable. As a result, CDS market could be used to calibrate certain model parameters that are usually assumed to be exogenously fixed in empirical applications. More specifically, this is the case of the recovery rate parameter. Estimation of CDS implied recovery rates would allow for the investigation of the informational content of the CDS market on this key parameter.

Credit spreads are determined by probabilities of default and recovery rates. Although the specification of recovery rate is one important determinant of the credit spread level, most of the empirical applications of structural models assume exogenously fixed recovery rates in order to assess credit spreads. Recovery rates are usually set to average historical rate of 40% or 51.31% (Ericsson et al. 2007, Huang and Huang, 2003) or adjusted to historical rates by industry (Alonso et al., 2008). Still, there are studies that suggest the existence of cyclical interdependence between probabilities of default and recovery rates. For example, Altman (2006) finds negative correlation between default rates and recovery rates. This means that CDS spreads will not reflect only the probabilities of default but also the changing expectations of recovery in the case of default. Namely, CDS spreads are market prices dependent on assumption on recovery rates and therefore should reflect market participant's expectations about its developments. For example, in bad times, when probabilities of default across reference entities rise, it is likely that recovery rates that investors exposed to credit risk expect to receive in the case of default will be lower.

Appendix

Appendix A

The Forte (2009) Methodology

The market value of total assets at any time t, V_t, is assumed to evolve according to the continuous diffusion process

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dz_t, \tag{A.1}$$

where μ is the expected rate of return on asset value, δ is the fraction of the asset value paid out to investors, σ is the asset return volatility, and z is a standard Brownian motion. Default occurs whenever V_t reaches a specific critical point V_b, defined in this case as a fraction β of the nominal value of the total debt P. With this modification of the original Leland and Toft (1996) model, at any t, the value of a bond with maturity τ, principal $p(\tau)$, and coupon $c(\tau)$, will be expressed as:

$$d(V_t, \tau) = \frac{c(\tau)}{r} + e^{-r\tau}\left[p(\tau) - \frac{c(\tau)}{r}\right][1 - F_t(\tau)] + \left[(1-\alpha)\beta p(\tau) - \frac{c(\tau)}{r}\right]G_t(\tau), \tag{A2}$$

where r is the risk-free rate, $\alpha \in [0,1]$ represents the bankruptcy costs, and

$$F_t(\tau) = \Phi[h_{1t}(\tau)] + \left(\frac{V_t}{V_b}\right)^{-2a} \Phi[h_{2t}(\tau)],$$

$$G_t(\tau) = \left(\frac{V_t}{V_b}\right)^{-a+z} \Phi[q_{1t}(\tau)] + \left(\frac{V_t}{V_b}\right)^{-a-z} \Phi[q_{2t}(\tau)],$$

with,

$$q_{1t}(\tau) = \frac{-b_t - z\sigma^2\tau}{\sigma\sqrt{\tau}}; \qquad q_{2t}(\tau) = \frac{-b_t + z\sigma^2\tau}{\sigma\sqrt{\tau}};$$

$$h_{1t}(\tau) = \frac{-b_t - a\sigma^2\tau}{\sigma\sqrt{\tau}}; \qquad h_{2t}(\tau) = \frac{-b_t + a\sigma^2\tau}{\sigma\sqrt{\tau}};$$

$$a = \frac{r - \delta - \frac{\sigma^2}{2}}{\sigma^2}; \qquad b_t = \ln\left(\frac{V_t}{V_b}\right); \qquad z = \frac{\sqrt{(a\sigma^2)^2 + 2r\sigma^2}}{\sigma^2}.$$

The total value of the debt $D(V_t)$ will be equal to the sum of all individual bonds outstanding. Accordingly, for N issued bonds with τ_n being the maturity of the *n*–th bond, the total value of debt will be:

$$D(V_t) = \sum_{n=1}^{N} d(V_t, \tau_n). \tag{A.3}$$

Finally, the total market value of the equity $S(V_t)$ will be expressed as:

$$S(V_t) = V_t - D(V_t | \alpha = 0), \tag{A.4}$$

where $D(V_t | \alpha = 0)$ is the value of the total debt when bankruptcy costs equal zero. This expression follows from the reasoning that the presence of bankruptcy costs affects only creditors.

Credit Spread Estimation

The theoretical credit spread at time t is determined as the premium from issuing at par value a hypothetical bond with the same maturity as the corresponding CDS contract – in this case, 5 years. This bond is assumed to pay a coupon $c_t(5, p)$, so that the following equation holds:

$$d(V_t, 5 | p) = p. \tag{A.5.a}$$

Accordingly, the bond yield is

$$y_t^E(5) = \frac{c_t(5, p)}{p}, \tag{A.5.b}$$

and consequently the theoretical credit spread is determined as the difference between the yield of this hypothetical bond and the corresponding risk-free rate:

$$ICS_t = y_t^E(5) - r_t \,. \tag{A.5.c}$$

Volatility, bankruptcy costs, and the default point indicator, are assumed to be constant. The nominal value of total debt P_t is approximated with the sum of short (STL_t) and long-term liabilities (LTL_t):

$$P_t = STL_t + LTL_t \,; \quad t = 1, \dots, T \,. \tag{A.6}$$

The pay-out rate, δ_t, is expressed as the ratio of interest and dividend payments to the total asset value at t,

$$\delta_t = \frac{IE_t + CD_t}{V_t} \,; \quad t = 1, \dots, T \,. \tag{A.7}$$

In order to determine $D(V_t|\alpha = 0)$, it is assumed that at each point t, the company has 10 bonds: one with a maturity of one year and face value equal to STL_t, and nine with maturities from 2 to 10 years, each with a face value equal to 1/9 of LTL_t. The coupon of each bond is determined as the fraction of IE_t proportional to the weight of its face value relative to the face value of total debt. The risk-free rate for each bond is fixed according to the swap rate for the corresponding maturity.

For an assumed initial arbitrary value of β, constant volatility σ and the series of total firm assets value V_t are simultaneously estimated on the basis of the following algorithm:

1) Proposing an initial value for σ, σ_0;
2) Estimating V_t series using the information on the stock market capitalization S_t, so that (A.4) holds for all t;
3) Estimating new volatility σ_1 from the obtained V_t series;
4) End of the process if $\sigma_1 = \sigma_0$. Otherwise, σ_1 is proposed at step 1.

The process is repeated until convergence is achieved.

In line with Leland (2004), bankruptcy costs are assumed constant and equal to $\alpha = 0.3$. As a result, different ICS series can be estimated on the basis of equation (A.5), depending on the value imposed for the default point indicator, β. In order to calibrate this value, the following relationship between ICS and CDS series is assumed:

$$ICS_t = CDS_t \times e^{\varepsilon_t}\,, \tag{A.8}$$

where ε_t are *i.i.d.* error terms with $E[\varepsilon_t] = 0$ and $Var(\varepsilon_t) = \sigma_\varepsilon$. Consequently, the Mean Squared Error (MSE) becomes the natural measure of discrepancy between credit spread series.

$$MSE = \frac{1}{T}\sum_{t=1}^{T}\left[log\left(\frac{ICS_t}{CDS_t}\right)\right]^2. \tag{A.9}$$

Finally, the default point indicator β is determined such that the divergence between credit spread series is minimized:

$$\beta \equiv \underset{\beta}{argmin}(MSE)\,. \tag{A.10}$$

Appendix B

The derivative of the transformation $g(V_t;\sigma,\beta)$ is given by:

$$\frac{\partial g(V_t;\sigma,\beta)}{\partial V_t} = \frac{\partial[V_t - D(V_t|\alpha = 0;\sigma,\beta)]}{\partial V_t} = 1 - \sum_{n=1}^{N}\frac{\partial d_n(V_t|\alpha = 0;\sigma,\beta)}{\partial V_t}, \tag{B.1}$$

where

$$\frac{\partial d_n(V_t|\alpha = 0,\tau_n;\sigma,\beta)}{\partial V_t} = -e^{-r\tau_n}\left(p_n - \frac{c_n}{r}\right)\frac{\partial F_t(\tau_n)}{\partial V_t} + \left(\beta p_n - \frac{c_n}{r}\right)\frac{\partial G_t(\tau_n)}{\partial V_t}, \tag{B.2}$$

and

$$\frac{\partial F_t(\tau_n)}{\partial V_t} = f(h_{1t})\frac{\partial h_{1t}}{\partial V_t} - \left[\frac{2a}{V_b}\left(\frac{V_t}{V_b}\right)^{-2a-1}\right]\Phi(h_{2t}) + \left(\frac{V_t}{V_b}\right)^{-2a} f(h_{2t})\frac{\partial h_{2t}}{\partial V_t};$$

$$\frac{\partial G_t(\tau_n)}{\partial V_t} = \left[\frac{-a+z}{V_b}\left(\frac{V_t}{V_b}\right)^{-a+z-1}\right]\Phi(q_{1t}) + \left(\frac{V_t}{V_b}\right)^{-a+z} f(q_{1t})\frac{\partial q_{1t}}{\partial V_t} +$$

$$+\left[\frac{-a-z}{V_b}\left(\frac{V_t}{V_b}\right)^{-a-z-1}\right]\Phi(q_{2t}) + \left(\frac{V_t}{V_b}\right)^{-a-z} f(q_{2t})\frac{\partial q_{2t}}{\partial V_t};$$

with

$$\frac{\partial h_{1t}}{\partial V_t} = \frac{\partial h_{2t}}{\partial V_t} = \frac{\partial q_{1t}}{\partial V_t} = \frac{\partial q_{2t}}{\partial V_t} = -\frac{1}{V_t\sigma\sqrt{\tau_n}}.$$

Appendix C

In this case we provide exact expressions for $A(\tau_n)$ and $B(\tau_n)$:

$$A(\tau_n) = \frac{2f\left(a\sigma\sqrt{\tau_n}\right)}{\sigma\sqrt{\tau_n}} + 2a\Phi\left(a\sigma\sqrt{\tau_n}\right); \tag{C.1}$$

$$B(\tau_n) = (a-z)N\left(-z\sigma\sqrt{\tau_n}\right) + (a+z)N\left(z\sigma\sqrt{\tau_n}\right) + \frac{2f\left(z\sigma\sqrt{\tau_n}\right)}{\sigma\sqrt{\tau_n}}. \tag{C.2}$$

Appendix D

The equity pricing equation in Brockman and Turtle (2003) is given by:

$$\begin{aligned} S_t(\tau) = {} & V_t\Phi(a_t) - Pe^{-r\tau}\Phi\left(a_t - \sigma\sqrt{\tau}\right) - V_t\left(\frac{V_b}{V_t}\right)^{2\eta}\Phi(b_t) \\ & + Pe^{-r\tau}\left(\frac{V_b}{V_t}\right)^{2\eta-2}\Phi\left(b_t - \sigma\sqrt{\tau}\right), \end{aligned} \tag{D.1}$$

where

$$a_t = \begin{cases} \dfrac{\ln\left(\frac{V_t}{P}\right) + \left(r + \frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}}, & for\ P \geq V_b \\ \dfrac{\ln\left(\frac{V_t}{V_b}\right) + \left(r + \frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}}, & for\ P < V_b \end{cases}$$

$$b_t = \begin{cases} \dfrac{\ln\left(\dfrac{V_b^2}{PV_t}\right) + \left(r + \dfrac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}}, & for\ P \geq V_b \\ \dfrac{\ln\left(\dfrac{V_b}{V_t}\right) + \left(r + \dfrac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}}, & for\ P < V_b \end{cases}$$

and

$$\eta = \frac{r}{\sigma^2} + \frac{1}{2}.$$

For tractability purposes, and in line with other empirical studies, rebate of zero for the original model is assumed. Finally, the derivative of the transformation is as follows:

$$\begin{aligned} \frac{\partial S_t(V_t;\sigma,V_b)}{\partial V_t} &= \Phi(a_t) + V_t f(q_{1t})\frac{\partial a_t}{\partial V_t} - Pe^{-r\tau} f\left(a_t - \sigma\sqrt{\tau}\right)\frac{\partial a_t}{\partial V_t} \\ &+ (2\eta - 1)\left(\frac{V_b}{V_t}\right)^{2\eta} \Phi(b_t) - V_t\left(\frac{V_b}{V_t}\right)^{2\eta} f(b_t)\frac{\partial b_t}{\partial V_t} \\ &- Pe^{-r\tau}(2\eta - 2)\left(\frac{V_b}{V_t}\right)^{2\eta-3}\left(\frac{V_b}{V_t^2}\right)\Phi\left(b_t - \sigma\sqrt{\tau}\right) \\ &+ Pe^{-r\tau}\left(\frac{V_b}{V_t}\right)^{2\eta-2} f\left(b_t - \sigma\sqrt{\tau}\right)\frac{\partial b_t}{\partial V_t}, \end{aligned} \tag{D.2}$$

where

$$\frac{\partial a_t}{\partial V_t} = \frac{1}{V_t\sigma\sqrt{\tau}}; \qquad \frac{\partial b_t}{\partial V_t} = -\frac{1}{V_t\sigma\sqrt{\tau}}.$$

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