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Alternative Determinants of Credit Default Swap Premia: Altman's Z and the empirical components approach

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Acknowledgements

As this is my last major piece of coursework at the University of Lund I feel that I should write something here[1]. First of all I would like to recognize my parents who are always there for me, thanks for letting me walk my own way. I am also eternally grateful to all of my friends who have made my time in Lund extremely enjoyable, you know who you are. I would also like to thank my supervisor, Hossein Asgharian, you seem to have an answer to everything. I would also like to give a special thanks to a person without whom I would not be an economist today. Although you probably considered me something of a slacker, which I was, I thoroughly enjoyed being your student for three years. Don't go belly-up Matt! Now, for those of you who are actually interested in credit derivatives, turn the page!

"I would rather be vaguely right, than precisely wrong."
-J.M. Keynes

"Show me the tuna!!"
-Matt McGee

[1] Also in order to fill the required number of pages!

Abstract

This paper conducts an empirical study of the determinants of credit default swap (CDS) prices. By using a new set of CDS quotes and explanatory variables for thirty major corporations, a set of linear panel data regressions are performed. The study confirms earlier research where risk free interest rate, volatility and leverage are found to be highly significant. In addition to this, a new variable, Altman's Z-score, is introduced and found to have a significant effect on the CDS price. The Z-score is introduced as a potential substitute for leverage and the two variables are hence compared in terms of significance and explanatory power. It is found that the Z-score is inferior to leverage in explaining the changes of the CDS price for one firm over time. However, for inter-firm cross-sectional analysis, the Z-score outperforms leverage. Hence, the conclusion is that Altman's Z-score and leverage have different strengths and that the variable to use is best chosen considering the type of study at hand.

Glossary

Altman's Z-score	A statistic using a combination of financial ration to predict the default probability of a firm.
CDS Spread	Equivalent to *CDS Price*
CDS Price	The price at which a CDS is quoted. Measured in basis points of the notional amount of the contract.
CDS Premia	Equivalent to *CDS Price*
CDS Quote	Equivalent to *CDS Price*
Credit Default Swap	The simplest and most common credit derivative which constitutes an insurance against a decrease in the value of bonds due to default of the issuer. The price is quoted in basis points of the notional amount protected.
Credit Derivative	A derivative product which has the purpose of transferring credit risk between different parties.
Credit Event	An event triggering the payout of a CDS contract. Usually a bankruptcy.
Credit Risk	The risk of now getting repaid on outstanding loans due to default of the counterparty.
Credit Spread	See *Z-spread*
Default Point	A statistic of *Moody's KMV*, which defines the point where a firm is likely to default. This is defined as a point where the asset value of the firm equals the par value of short term debt plus half of the long term debt.
Default Risk	The risk that a corporation will become bankrupt.
Distance to Default	One of the statistics in *Moody's KMV*, measuring how many standard deviations exist between a firm's expected value and its *default point*.
Empirical Components Approach	An approach for explaining CDS prices through regressions of explanatory market variables on CDS prices.
Geometric Brownian Motion	A type of time series process often used to illustrate the value of a firm. Each consecutive move is independent of the last.

Long Position	Having a long position means to something means that you have a positive exposure to it and will gain if it increases in value.
Moody's KMV	A well known commercial *structural model* for predicting default probabilities.
Notional Amount	The face value of bonds that are protected using a CDS.
Reduced Form Model for CDS Pricing	A model for determining the appropriate price of a CDS based on the information inherent in the prices of existing bonds issued by the reference entity.
Reference Entity	The issuer of the underlying bond in a credit derivatives contract. Usually a corporation or a government.
Repo Market	The market for borrowing money while using bonds as security in order to get a better rate. Also used by market participants who wish to borrow specific bonds.
Short Position	Opposite of *long position.*
Structural Model	A type of model for predicting the risk of default of a company and pricing its debt by viewing the debt as a risk free bond and a short put option. Originally suggested by Merton (1974).
Z-Score	See *Altman's Z-score*
Z-Spread	The spread over the risk free rate acquired from owning a risk-bearing bond.

1. Introduction

This section starts by introducing the reader to the growing market for credit derivatives and credit default swaps. Furthermore, the reader is given a background to the research surrounding the study conducted. This is followed by a statement of purpose and a hypothesis. Finally, the limitations and structure of the paper are explained.

1.1 Credit Derivatives

Credit derivatives are derivative products with debt (credit) as underlying asset. By taking a position in credit derivatives, an investor can choose the size of his exposure to credit risk. The issuer of the bond which is used as underlying is commonly referred to as the *reference entity*. The simplest way of viewing a credit derivative is as insurance for lenders of money. Therefore, one part in a transaction is long credit risk and one part is short credit risk. The former is called *protection seller* and the latter is called *protection buyer*.

The market for credit derivatives is relatively new and still unknown to most people. In the secluded world of high finance however, credit derivatives is the new buzz-word and the volumes traded in these products are growing with incredible speed. The products were introduced to the marketplace by a small group of investment banks[2] in the mid 1990's and have today grown to become one of the biggest international markets with a projected volume of $40 trillion notional outstanding by the end of 2006[3]. This makes it comparable in size to the entire cash bond market. The biggest product by volume is the credit default swap which has retained a market share of close to 50 percent of volume in the credit derivatives market. *Figure 1* illustrates the growth of credit derivatives compared to corporate debt.

[2] FT Magazine, March 25/26 2006, *The Dream Machine,* pp. 20-26
[3] Global Finance, New York: Jan 2006 Vol. 20, Iss. 1; p.8

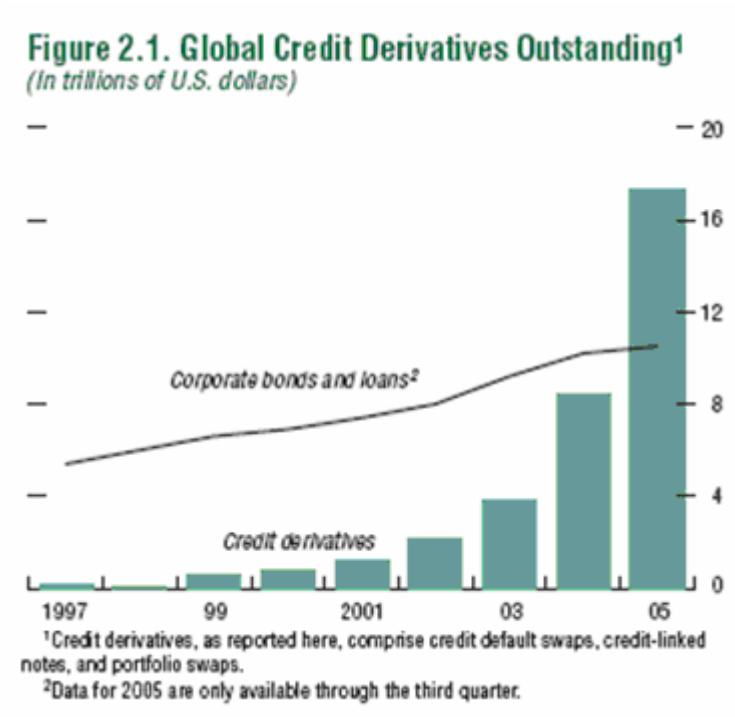

Figure 1: A comparison of market size: Credit derivatives and Corporate Bonds. Source: IMF Global Financial Stability Report 2006

1.2 Subject of study

This paper will focus on the credit default swap which is by far the most traded credit derivative. The CDS is also the most vanilla credit derivative available, vanilla meaning standardized and simple. Continuing to look at credit derivatives as ways to reduce exposure to credit risk, the CDS is a standard insurance policy. The buyer of protection pays a premium to the third party protection seller and receives a large payout in case of default of the counterparty.

The majority of CDS contracts are traded with large public companies or governments as reference entity. Other credit derivatives are usually variations of the CDS principle. For example protection against an index of corporate debt or different ways to limit the protection offered by the contract. Therefore, in valuing credit derivatives, the CDS is the least complicated product and usually the starting point.

1.2.1 Problem specification and purpose

From existing models for valuation of a CDS, a number of important variables can be extracted. More specifically, so called structural models often quote volatility, risk free rate and firm leverage as the three most important factors in determining the price of a CDS. Earlier studies have been made where these and other factors are used as explanatory variables in regressions trying to explain levels and variations in CDS premium[4]. This paper will label this method *the empirical components approach* (ECA). Due to the relative infancy of the CDS market, low liquidity and volume has made it difficult to access large and synchronous price samples[5]. Earlier research has therefore often been forced to interpolate between quotes or restrict the sample size in their studies of the empirical components. This study will apply the ECA and in a similar way to earlier papers attempt to explain variations in CDS prices using observable market variables. The data used for CDS prices is taken from Datastream and is quoted on daily basis. It dates back three years, giving a comparably large sample size. Four explanatory variables are employed; risk free rate, volatility, leverage and Altman's Z-score.

[4] For examples of such studies, see Collin-Dufresne et al (2001), Campbell and Taksler (2003), Benkert (2004), Cremers et al (2004) and Ericsson et al (2004).
[5] In this paper, the words *price* and *premium* are used interchangeably for CDSs. The price of a CDS is quoted as a number of basis points.

The effects of volatility, leverage and risk free rate have already been tested and this study aims to confirm their effect on a new data set. The new variable which is introduced is Altman's Z-score which is compared to leverage in terms of explanatory power. The Z-score is a measure combining different key ratios in order to give an indication of the probability of default for a corporation. Hence, this measure includes more factors concerning the financial health of a corporation compared to leverage and may be appropriate as a substitute. This paper therefore tests whether Altman's Z-score can achieve a higher explanatory power than leverage. There have been no previous attempts to apply Altman's Z-score in the ECA. A successful application of the variable would therefore have the potential for new conclusions regarding CDS prices and further research.

1.2.2 Hypothesis

The hypothesis of this paper is that the introduction of Altman's Z as an explanatory variable for CDS prices will increase the explanatory power of existing models. Furthermore, the effects of leverage, risk free rate and volatility are predicted to be significant and consistent with earlier studies in explaining CDS prices. In short, this paper uses the empirical components approach to explain CDS prices on a new data set for thirty major corporations. The traditional explanatory variables volatility, leverage and risk free rate are tested to see if their effect confirm earlier results. Furthermore, the variable Altman's Z-score is introduced as an alternative to leverage. The aim is to investigate whether the Z-score has properties which may complement or even replace leverage as an explanatory variable.

1.3 Limitations

The method employed is linear regressions with panel data where the effects of the different variables are tested. The paper is limited to testing effects for thirty major corporations between the beginning of 2003 and the end of 2005. The time interval was chosen to ensure availability of CDS data. Furthermore, because the paper uses certain key ratios from the balance sheet as part of the Z-score, the frequency of observations was limited by the number of report dates. In order to maximize the number of observations, corporations were chosen so that quarterly data would be available. This limited the sample to U.S. and European firms with an emphasis on the former. An alternative approach employed in similar studies is the interpolation of balance sheet data over the year to achieve daily frequency. The author of this paper chose not to apply such a method as the sample was already large enough to draw meaningful conclusions and the method risks creating a bias due to false assumptions. Furthermore, the model proposed does not aim to produce accurate predictions of CDS prices. The purpose is instead to gain an understanding of how *changes* in the chosen variables affect CDS prices. Although a level regression is performed, the focus is on the regressions measuring the dynamic relationship between the changes in explanatory variables and CDS prices. The reason for not focusing on the levels is that the data sample is not well suited for such an analysis as we have relatively few observations per period studied.

1.4 Outline

Section 2 will provide a more detailed explanation of the properties of credit default swaps. It will also give the reader a background of the research on this and related subjects. Finally, it describes and briefly compares different methods of valuing CDS contracts. Section 3 gives a motivation for the study and the method employed. The section then proceeds to describe the method further, including regression techniques and explanations of the variables in the data set. Section 4 offers a more detailed description of the data including formatting, sources and other characteristics. Section 5 presents and briefly comments the results of the regressions performed. Section 6 proceeds with a more thorough discussion of the results and links them to the hypothesis. Section 7 concludes the paper and provides suggestions for further research.

2. Theory and background

This section gives the reader additional understanding of the market for credit derivatives. Furthermore, the design of a Credit Default Swap is given a treatment along with a discussion of its specific properties. A background is also given to the earlier research and pricing models within the field of credit and credit derivatives.

2.1 Credit derivatives and the market structure

When buying corporate debt in the marketplace, an investor effectively becomes long the credit risk of the issuing corporation. The credit derivatives contracts available enable the investor to offset the credit risk of the corporate debt by buying protection. It is important to see the difference between taking a long position in credit risk by selling protection and taking it by buying a corporate bond. In buying a corporate bond the investor exposes himself to a variety of risks (notably interest rate risk) whereas a seller of protection exclusively deals in credit risk.

The possibility of taking positions in credit risk without getting exposure to other risks[6] has attracted many participants to the market and is the reason for the rapid growth of credit derivatives. The largest group of investors is banks. In 2004 they accounted for more than half of the protection buying and 38 percent of the selling. The big issuers in the bank sectors include investment banks who wish to increase their exposure to risk or have the possibility to hedge their exposure in the bond markets. Other major participants are hedge funds and security houses who use credit derivatives to optimize their portfolios. This is done either by hedging their positions or by taking outright views on the credit-worthiness of debt.

[6] This is not entirely true. A position in credit derivatives always includes counterparty risk. This is especially true for the buyer of protection. The statement refers to the possibility to avoid e g interest rate risk.

The credit derivatives are also interesting to investors because they allow them to express more complex market views. Examples are capital structure views – senior debt versus subordinate debt, rating views – B-rated debt versus BB-rated debt and correlation views – the correlation between defaults of corporations in a sector/country. Additionally, insurers and re-insurers trade large volumes of credit derivatives. They are large sellers of protection and use their expertise in calculating risk probabilities to expand into the financial markets[7].

2.2 Credit Default Swaps

The credit default swap instrument is by far the most common instrument in the markets for credit derivatives. Although there are many different products in these markets, most are just simple variations of the CDS. The CDS is in essence nothing more than an insurance policy on the value of a bond where the policy kicks in when the issuer defaults on its debt. The exact terms and definitions of default are specified in the agreement and this kind of event is commonly referred to as a *credit event*. When a credit event occurs, the buyer of protection is compensated by the seller with the difference between the par value of the bond and the current market value. The early CDS contracts specified that the bond should be delivered by the protection buyer in return for the par value. Nowadays most deals are settled in cash and the market values of the bonds are determined by third parties. This enables market participants such as hedge funds to express market views on credit risk without ever owning the underlying credit. *Figure 2* illustrates the cash flows involved in a CDS transaction. *Figure 3* depicts the composition of the credit derivatives market as of September 2004.

[7] Statements about numbers and composition of the credit derivative markets are taken from the British Bankers' Association Credit Derivatives Report (Executive Summary) 2003/2004 and the Merrill Lynch Credit Derivative Handbook 2003.

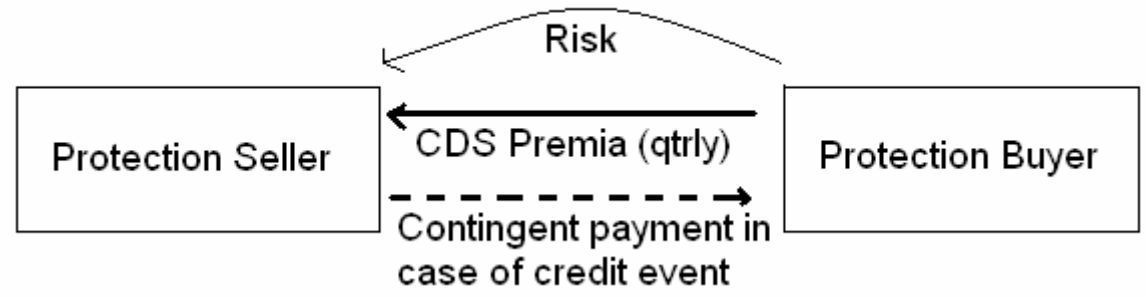

Figure 2: Cash flows involved in a standard CDS contract.

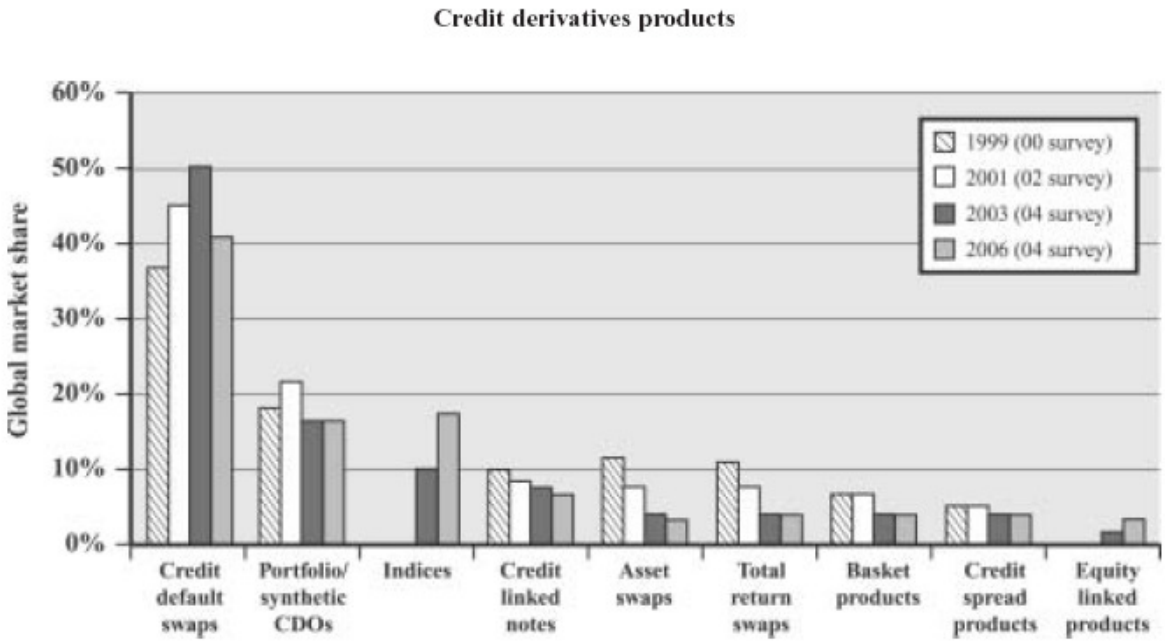

Figure 3: The composition of the Credit Derivatives markets by market share. [8]

[8] Credit Derivatives Report 2003/2004 Executive summary, British Bankers Association, September 2004

2.1.1 Credit Default Swaps and Bond spreads

In a classic paper, Merton (1974) stated that a corporate bond can be viewed as a combination of a owning a risk-free bond and issuing a put option on the value of a firm's debt. Consequently, the excess return of a corporate bond over the risk-free rate equals the price of the put option. A CDS contract is very similar to such a put option and therefore has a price which must be close to the bond spread of the reference entity over the risk-free rate.

The issuer of a CDS (left hand side in *Figure 2*) therefore has a credit risk profile of owning a corporate bond whereas the investor on the right hand side who buys the CDS has a credit risk profile equal to that of shorting a corporate bond. Perhaps more intuitively, we can say that buying a corporate bond and at the same time buying insurance in the form of a CDS should yield the same net return as owning a risk free bond. This is illustrated in *Figure 4.*

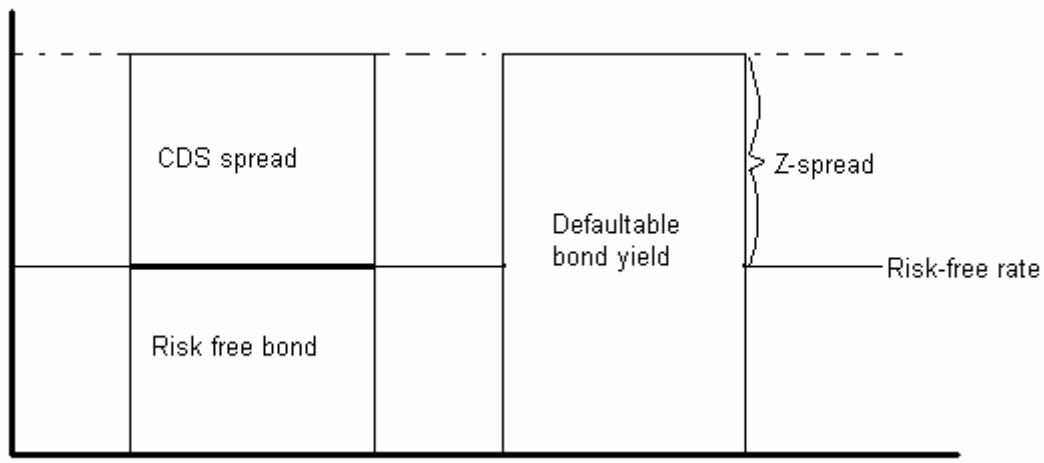

Figure 4: The theoretical relationship between CDS premium and credit spread

Furthermore, if we look at the combination of owning a risk free bond and selling CDS protection, the cash flows should equal those from owning the corporate bond of the reference entity. However in practice, there are a number of factors which make slight divergences from this possible. The difference between CDS spread and the Z-spread is called basis and may exist for a number of different reasons.

2.1.2 Basis between CDS prices and bond spreads

CDS contracts, like other swaps, are priced so that there is no initial payment or intrinsic value of the contract upon initiation. Also, the most common contracts are designed to have the maturity of five years from the day the deal is made. Therefore, CDS prices become the equivalent of Z-spreads for bonds with a constant maturity of five years that always trade at par. Duffie (1999) concluded that the theoretical relationship of *Figure 4* is only valid for floating rate notes that are currently trading at par. Needless to say this creates a source of basis between the assets. Nevertheless, this effect is comparably small and Duffie (1999) proceeds by showing that this bias is not sufficiently large to explain the empirically observed basis in the market.

Other structural differences creating basis are embedded options in corporate bonds, differing coupon conventions between a CDS and a bond as well as the fact that coupons may be treated differently upon a credit event. A bond with an option making it callable by the issuer has a lower value because it limits the rights of the lender. Day count conventions are also a factor to consider. A standard CDS premium is paid A/360 whereas corporate bonds usually pay 30/360. Upon default, a CDS normally does not compensate the holder for the aggregated interest on the reference entity whilst this is normally part of the claim by the bondholder to the issuer.

Other important sources of basis are the more market-oriented factors. In the case of negative basis, a higher Z-spread than the CDS-spread, an investor could make theoretical arbitrage by borrowing at the risk-free rate, investing in the bond at the same time as buying protection. This is not an implausible scenario and we might expect large institutional investors to take advantage of such opportunities, should they arise. For a positive basis, however, the process is not quite as simple. The bond is now expensive compared to the CDS and the theoretical arbitrage would be made by shorting the bond, issuing the CDS and investing at the risk-free rate. The problem with this is that it requires the trader to be able to short the reference entity more or less without cost. This is not realistic for a market participant who does not own the bond as it entails borrowing it in the repo market. For corporate bonds with relatively small issues compared to governments, this usually entails a difficult search process, short repo maturities (usually one day) and high costs. Even if an investor is able to fund himself at close to the risk-free rate it is not uncommon to have to pay over 100 basis points for a reverse repo in the bond. This creates an inherent rigidity in any positive basis in the CDS market.

Naturally, market participants owning the reference entity could sell their holdings and instead issue a CDS and invest at the risk-free rate. This trade would have the same effect as the arbitrage in eliminating the bias. This does not occur on any large scale and the reasons are likely to be a combination of factors, one of which may be the nature of bondholders. One part of the group are passive investors and are therefore not aware of the opportunity, another is indeed aware but is restricted by turnover limitations or restrictions regarding the use of derivatives. A second factor may be that the size of holdings may be limited to relatively small amounts. CDS contracts are usually traded in sizes of $10 million notional, which may make it hard for investors to match their exposures.

Another factor worth mentioning is that the CDS is not a perfect hedge against credit risk as there is always a counterparty risk involved. This also acts to reduce the price of the CDS. Furthermore, a liquidity premium on either asset may create a discrepancy in the pricing. Longstaff et al (2004) study the components of corporate yield spreads and find that the two main components are default risk and liquidity premium, with default risk being the dominating component. Hence a difference in the liquidity premium between the CDS and the bond is likely to create a bias.

The combination of factors stated above help to explain the reasons why CDS contracts and corporate bonds usually trade at a small basis. Note, however, that these factors are comparably small and that the CDS spread and the Z-spread are both good proxies for credit risk that are affected by mostly the same factors. This is important to remember as the models for CDS-spreads presented in this paper are largely based on models of the Z-spread.

2.2 Valuation models

Because the market for Credit Default Swaps has grown rapidly during the last years, a significant body of research has emerged on the subject of valuation. Essentially, the valuation of a CDS is very similar to determining the appropriate bond spread over the risk free rate. A method for this was formalized by Merton (1974) whose work is still today part of the foundation used to value credit derivatives. The type of model created by Merton (1974) has come to be known as a structural model and has been developed and modified ever since[9]. Merton viewed equity as a call option on the value of a firm which makes it possible to value the option according to the principles laid out by Black and Scholes (1973).

[9] The well –known Moody's KMV model which is used to asses default risks in companies today is indeed entirely based on the model first suggested by Merton (1974).

As a consequence of this, the debt of a corporation can be viewed as a risk-free bond plus a short position in a put option on the value of the firm. The price of the put option then becomes equivalent to the risk-premium on the corporate bonds and can also be determined using a common option pricing formula. This method is called the structural approach for determining credit spreads. Once again, for all purposes of this study, we can view the corporate bond spread over the risk-free rate to be interchangeable with the price of a CDS. Therefore, the structural model approach is commonly applied to both CDS contracts and corporate bond spreads. In addition to the structural models, another set of models for setting CDS prices has emerged during recent years. These models are called *reduced form* and take a less academic approach to valuation in that they do not attempt to explain the underlying factors of CDS prices. The reduced form model for CDS pricing was introduced by Jarrow and Turnbull (1995). In addition to reduced form and structural models there are other pricing models available. A notable example is JPMorgan's CreditMetrics which bases the pricing on the probability of a corporation moving from one credit rating to another. Nevertheless, this section will limit itself to describing structural and reduced form models.

2.2.1 The structural models

Beginning with Merton (1974), the structural models of credit spreads gained momentum during the seventies and were adjusted and improved in numerous papers in order to fit reality better. Building on the work of Black and Scholes (1973), Merton (1974) modelled the assets of a firm to follow a log-normal process where the firm would default if the value went below a specific level, called the default boundary. As a consequence, the equity of the firm could be viewed as a call option on the assets of a firm. Continuing this reasoning enabled Merton (1974) to also price the debt as an option and thereby extract its value.

Today, a large part of the academic research on credit spreads and credit derivatives still build on the principles suggested by Merton (1974) and there are several commercial models available that are based on his work. In practice, what characterizes the structural models of credit spreads compared to the reduced form models is the practical use of real economic variables.

The basic postulate proposed by Merton (1974) was to look at the firm value (*V)* as the value of a single equity issue (*E*) and a single zero-coupon bond (*F),* maturing at *t=1,* with face value *b*.

$$V^t = E^t + F^t \qquad \textit{Equation 1}$$

Therefore, if the value of the firm exceeds *b* at time *t(1),* it will pay off its loans and the remaining value will belong to the stockholders. If the value of the debt is larger than the value of the firm, the bondholders will liquidate the firm's assets and the equity becomes worthless.

$$E^1 = \max(V^1 - b, 0) \qquad \textit{Equation 2}$$

The expression in *Equation 2* is identical to the payoff from a call option with strike *b* and the firm's value as underlying. This is exactly the model suggested by Merton (1974). A direct consequence of this reasoning is that the debt of the firm can be viewed as a risk-free bond plus a short put option on the firm.

$$F^1 = b - \max(b - V^1, 0)$$ *Equation 3*

From *Equation 2,* it can be seen that the value of the debt at time *t(1)* equals *b* unless *b* exceeds the value of the firm. From this simple model, different assumptions can be made in order to value the debt and equity using the formula proposed by Black and Scholes (1973). *b* would equal strike price, *V* would equal price of underlying and *t(1)-t(0)* would be time to maturity. Volatility and the risk free rate can be acquired from observable market variables. The above representation presents the most basic version of a structural model. Note that it is of course an over-simplification to assume that the debt of a firm is a zero coupon bond with one specific maturity. It is also difficult to measure the firm value and its volatility.

2.2.2 A practical example: Moody's KMV[10]

Perhaps the most well-known current practical application of the structural model is the Kealhofer, MvQuown and Vasicek (KMV) model created by KMV Corporation which is now part of Moody's. The market value of a firm is solved for using the current market price of a firm.

$$E^t = f(V^t, \sigma_V, K.c, r)$$
$$\sigma_E = g(V^t, \sigma_V, K, c, r)$$ *Equation 4*

In *Equation 4,* notations are the same as above and σ_V denotes the volatility of asset value, σ_E denotes equity volatility, *K* denotes leverage ratio, *c* denotes average coupon paid and *r* denotes the risk free rate. The equations in *Equation 4* once again apply the view of equity as a call option in order to extract firm value and volatility of firm value.

[10] Description of the KMV model is taken mainly from the discussion in Crouhy et al (1999)

The KMV model defines the point of default as the point where asset value equals the par value of short term debt plus half of the long term debt. This approximation is based on empirical studies of hundreds of defaults. In addition, the expected value of the firm's asset value in one year is calculated by letting it follow a standard geometric Brownian motion plus a drift.

The third step of the analysis is to standardize the difference between the expected value of the firm's assets and the default point (DPT) using the volatility of the asset value. This creates a measure labelled Distance to Default (DD). The expression is illustrated in *Figure 5.*

$$DD = \frac{E(V_1) - DPT}{\sigma_V} \qquad \textit{Equation 5}$$

Figure *5* is an edited figure from Crouhy et al (1999) which illustrates the relationship between the different variables.

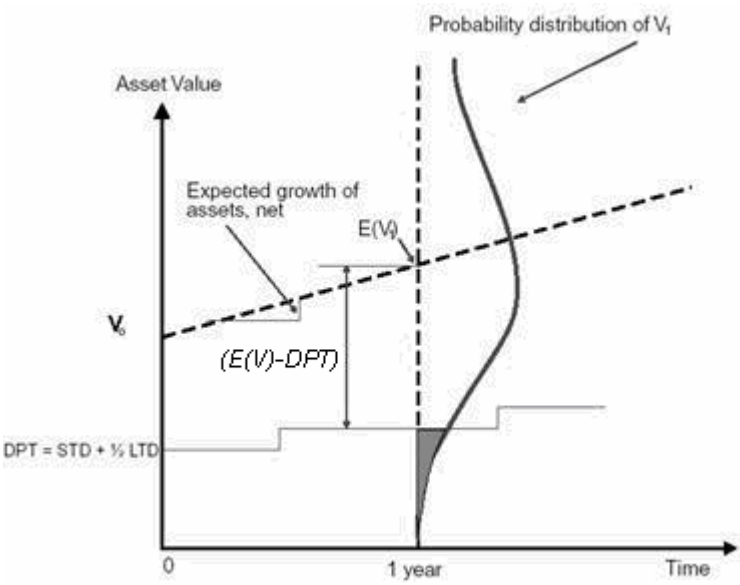

Figure 5: The relationship between the variables in the KMV-model. Source: Crouhy et al (1999), Note: the figure has been edited from its original form.

The last step of the KMV model is to derive the Expected Default Frequency (EDF). This is based on empirical observations of a large number of firms, where the DD has been calculated and the outcome observed. Based on these observations, a probability of default is arrived at. For application to credit spreads, the EDF can easily be combined with assumptions of recovery rate in case of default to calculate present values of expected cash flows from a bond and therefore also the appropriate bond spread[11].

In order too see how these structural models are applicable to CDS contracts one needs only consider the similarity of the two instruments. The corporate bond pays coupons according to credit risk and loses its value if the firm defaults. The seller of a CDS gets premia-payments and loses money at default. Also, the credit spread approximately equals the CDS spread. Therefore, the variables in a structural model will have the same impact on bonds and CDSs.

2.2.3 Reduced Form models

The second school of modelling credit-risk is more recent but has nevertheless received much attention. The reduced form approach has gotten its name because it assumes that the firm's default time is inaccessible or unpredictable and thereby treated as exogenous[12]. Instead of measuring market fundamentals, the approach for achieving credit spreads is based on the actuarial approach used by insurance companies in calculating such things as mortality rates.

[11] It is probably fair to say that the main difficulty in pricing CDS contracts and corporate bonds lies in estimating their probabilities of default.

[12] Arora et al (2005) An alternative to this view is presented by Jarrow and Protter (2004) who argue that the distinction is in terms of information. The structural models implicitly assume complete information about a firm whereas the reduced form models limit the information to that available in the marketplace. Irrespectively, reduced form models can be viewed as using relative pricing to a higher degree than fundamentals.

The basic concept is finding a functional form for default intensity of a firm which is defined as the first derivative of the probability of default with respect to time. This functional form is specified so that the default intensity is a function of corporate bond spreads. By inserting the market spreads, the implicit probability of default can then be extracted.

Hull and White (2000) suggest a reduced form model for the pricing of a standard CDS with no counterparty risk. The model uses assumptions about the expected recovery rate and the size of the claims by bondholders to acquire implicit probabilities of defaults in corporate bond spreads. By adjusting the CDS premia to make the expected payoff equal to zero, a fair value of the spread is decided. The expected recovery rate is acquired from historical values and the claim size is assumed to equal face value plus accrued interest in accordance with Jarrow and Turnbull (1995). In essence, this model is dependent on the existing prices available in the corporate bonds. Other notable contributions in the area are Duffie and Singleton (1999), Duffie, Pedersen and Singleton (2003) and Driessen (2004). The Reduced form models are by their nature very useful for valuing credit claims, as they are able to give more accurate predictions of prices[13]. On the other hand, they contain no information regarding the fundamental determinants of default probabilities.

[13] For a discussion of this, see Houweling and Vorst (2005)

2.2.4 The empirical components approach

Neither the reduced form nor the structural models are perfect in explaining the CDS spreads and there seems to be no consensus on the superiority of any one model. The reason for the failure to create definite model of credit spreads is that it would require an arbitrage opportunity that has not been found and may not exist. The structural models proposed in different papers seem to suggest the importance of the same three empirical factors for determining the Z-spread. These are financial leverage, volatility and risk-free term structure[14]. These factors and others have therefore been the subject of a new approach to analyzing Z-spreads and CDS premium.

Instead of building a classic structural model, Collin-Dufresne, Goldstein and Martin (2001)[15] extracted the components determining the price in structural models and used them for input in a regression. This attempt resulted in low explanatory power and significance but nevertheless constituted the first attempt at a new approach for explaining credit spreads. Campbell and Taksler (2003), Benkert (2004), Cremers et al (2004) and Ericsson et al (2004) continued on the same road. Their methods were similar in that they used different financial variables to explain the CDS premium in regressions. I will refer to this method as the empirical components approach (ECA). Campbell and Taksler (2003) uses panel data of bond prices in the nineties to explain the Z-spreads using historical equity volatility and credit rating. They find that the two factors used explain approximately one third of the spread levels each.

[14] Ericsson et al (2004) p. 3
[15] Henceforth referred to as CGM (2001)

Benkert (2004) and Cremers et al (2004) extend the work of Campbell and Taksler (2003) by concluding that option implied equity volatility has a higher explanatory power than historical volatility in explaining CDS premia. Ericsson et al (2004) focuses on a set of CDS spreads instead of Z-spreads and finds that equity volatility, firm leverage and risk-free rate explain 60 percent of the CDS level in the sample.

This paper presents an empirical components model where CDS spreads are explained by regressions of a number of variables similar to those of earlier studies. The method will be similar to that of Ericsson et al (2004) but we will use newer CDS quotes and introduce a new variable to try to reach a higher explanatory power. The academic and practical usefulness of this approach comes from its ability to directly test and even quantify the effect of the different explanatory variables. Thus, the aim of this paper is not to build a model that accurately predicts CDS prices, but rather to increase the understanding of which empirical factors have an effect on said prices. By doing this it is the hope of the author to increase general understanding of the constituents and determinants of CDS spreads as well as providing empirical results that may help in the creation and modification of future structural models.

3. Method

This section starts by giving a motivation for the model employed in this paper. Next, the model is specified and explained to the reader with added specifications for each variable.

3.1 Motivation

The empirical components method of explaining CDS spreads which will be used in this paper is as explained above a continuation of earlier research. The approach is different from the reduced form and structural models because it is merely an investigation of the effect of a few variables on CDS prices and not a complete model. The most obvious drawback would be that the resulting model is not likely to display any accurate predictive power for the entire CDS spread. The reason for this is that a regression is not likely to reach an explanatory power (e g R-squared) which is high enough to explain all changes in the spread. Nevertheless, the model is not without merits. The regression allows comparatively simple study of the effect of individual factors on the level of the CDS spread. We can also compare the relative effect of different variables. This in turn gives the researcher a possibility to gain a deeper understanding of the importance of different factors as well as test the significance of new ones.

Ericsson et al (2004) summarizes three different variables that seem to be recurring as significant in most studies. These factors are leverage, volatility and risk-free rate of return. By regressing these on the CDS levels, Ericsson et al (2004) manages to explain approximately 60 percent of the *level* of the CDS spread. This paper attempts to explain the CDS premium using similar fundamental variables, but using different proxies to measure them. The aim is to confirm the results of previous research on a new data set and to investigate the explanatory power of the explanatory variable Altman's Z-score. The Z-score is in particular compared to leverage in terms of explanatory power.

It is important to note, as pointed out by Ericsson et al (2004) that although the fundamental effects of these variables are the same on CDS prices and bond spreads, there are a few advantages with choosing the CDS data in making a study of this type. First of all, there is no need to calculate the Z-spread[16]. This may sound trivial, but calculating the Z-spreads requires a clear specification of the risk-free yield curve, which may be hard to proxy even if we are able to track its constant changes. The difficulty of finding the correct measure for risk-free rate is further addressed by Hull and White (2004). A second advantage of using CDS spreads is that they reflect the credit risk and nothing else. Other components of the bond spreads may obscure the impact of changes in credit risk.

3.2 Choosing the variables

In order to perform regressions and measure the effects of the chosen variables, it was important to carefully specify the data to be used. The volatility is calculated using daily equity returns during the 90 days prior to each data point. This method is similar to that of Ericsson et al (2004). Other papers have instead chosen implied equity option volatility as the proxy for volatility. The reason for this is that it may incorporate information about future expectations and may therefore contain more information[17]. It is also logical if we choose to, like Merton (1974)[18], think of a CDS as a put option on the value of a firm to use the option implied volatility. The reason why this paper uses historical equity volatility is that option data was not available for the companies studied. Furthermore, the focus of this paper is not to maximize explanatory power of the volatility but to confirm its effect on CDS prices. The second factor, leverage, is important because the default probability increases as the leverage ratio approaches unity. The calculation of leverage is specified in section 4.

[16] The Z-spread, as illustrated in figure *(4)* is the spread of corporate bond yield over the risk free rate of return.
[17] For examples of this method, see Benkert (2004) and Cremers et al (2004)
[18] Merton referred to the Z-spread in his famous paper. However, the principle is the same.

Theory also suggests that business climate may be an important factor for credit spreads. Therefore, instead of limiting the study to one ratio, Altmans Z-score[19] is used as a proxy for both leverage and business climate. The Z-score model was developed by Edward Altman in the late 1960's as a measure of default risk in a firm. By combining five different key financial ratios, Altman graded firms in terms of risk of default. The model has since been developed and the version used in this paper is presented below. Leverage and the Z-score were regressed separately as substitutes to explain changes in the CDS price.

Because the study employs fixed effects models, the most important contribution of an explanatory variable is the effect it has on the regressand *when it changes*. Therefore, one might find that it is not practically important whether one chooses e.g. the Treasury yield or the Swap rate as a proxy for the risk-free rate as they are likely to be moving together most of the time. Nevertheless, this paper uses the Swap rate minus ten basis points as suggested by Hull and White (2004).

3.2.1 Volatility

The historical equity volatility was acquired using the databases of Datastream. The data used consisted of daily closing prices for each of the firms. The volatility was calculated as the variance of the daily stock return for each period.

$$Daily\_return = r_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

$$Volatility = \sigma_{r_t} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t - \bar{r})^2} \qquad \textit{Equation 6}$$

Because the data is quarterly, *T* in *Equation 6* will be around 70 (business) days.

[19] Caouette et al (1998)

3.2.2 Altmans Z-score

In the field of insolvency prediction, few models if any have combined simplicity, innovation and efficiency in such an elegant way as Altman's Z-score. The model was originally suggested by Edward I. Altman in 1968 with the publishing of his famous paper *Financial Ratios, Discriminate Analysis and the Prediction of Corporate Bankruptcy* in the Journal of Finance. The Z-score of a firm is calculated using a multivariate model taking into account various financial ratios. The resulting value then puts the firm in a category to which Altman assigns a certain probability of default. The model is based on historical data for an original sample of 66 firms, of which 33 had filed chapter eleven bankruptcy. The analysis of Altman was focused on finding common characteristics of the firms that survived that differed significantly from the characteristics of those that went into bankruptcy. The resulting model contains five different ratios which are presented in *Equation 7*. *Equation 7* presents the ratios as they are combined in Altman's model[20].

$$1{,}2X_1 + 1{,}4X_2 + 3{,}3X_3 + 0{,}6X_4 + 1{,}0X_5$$

where

$$X_1 = \frac{Total\_current\_assets - Current\_liabilities}{Total\_assets}$$

$$X_2 = \frac{\mathrm{Re}tained\_earnings}{Total\_assets} \qquad \textit{Equation 7}$$

$$X_3 = \frac{Operating\_result}{Total\_assets}$$

$$X_4 = \frac{Total\_market\_cap}{Total\_liabilities}$$

$$X_5 = \frac{\mathrm{Re}venue}{Total\_assets}$$

[20] The model has been revised since its original form, the numbers used below are taken from Reuters 3000 Xtra and may be not be as exact as the original model proposed by Altman.

Z-score	Interpretation
>3,0	Default not likely
1,8-3,0	Gray area
<1,8	Likely to default

Table 1: Classifications in Altman's Z-score model

The classifications presented in *Table 1* are referring to bankruptcy within the next two years. The probabilities for each value are not of interest in this paper as we are measuring the differences in Altman's Z. The fixed-effects model will therefore investigate the effect of a changed Z-score of a firm on the CDS-premia. We expect a positive significant effect as a higher Z-score implies a higher likelihood of default which should increase the price of bond insurance.

3.2.3 Risk-free rate

The potential arbitrage demonstrated in diagram 3 states that the risk-free rate plus the CDS premia must equal the corporate bond yield. One of the problems that makes this an approximate rather than exact arbitrage is the specification of the risk-free rate. Hull and White (2004) conclude that although there is no consensus on which rate to use, the Swap rate minus ten basis points appears to be the market risk-free rate. This conclusion is reached by regressions using the assumptions based on the approximate arbitrage discussed earlier. Other studies use the U.S. treasury yield or unadjusted Swap rate.

Hull and White (2004) however, argue that the treasury yield is too low due to special tax treatment and that the Swap rate is too high because it contains a risk-premium. This paper will follow the recommendation of Hull and White (2004) and use the Swap rate minus ten basis points. Nevertheless, the choice of a different rate would probably not alter the results significantly as this paper studies the changes in the risk-free rate. Because the spread between the treasury and the Swap rate is usually stable, the changes are the same.

3.2.4 Leverage

The leverage is the second variable, along with Altman's Z which is not available daily. The leverage is calculated in accordance with earlier empirical components research as the value of total liabilities divided by the sum of total liabilities and market capitalization.

$$Leverage = \frac{Total\_Liabilities}{(Total\_Liabilities + Market\_Cap)} \qquad \textit{Equation 8}$$

3.3 The regression models

3.3.1 Pooled cross section (level)

One approach would be to explain the CDS premium, $S_{i,t}$, using the levels of equity volatility, $vol_{i,t}$, leverage, $lev_{i,t}$ Altman's Z-score, $Z_{i,t}$ and the swap rate minus ten basis points, rf_t. However, because it is panel data, pooling the observations and running a cross-sectional regression would produce the risk of heterogeneity bias. Such a regression would also assume a constant intercept over time and between different reference entities, which may not be plausible[21].

$$S_{i,t} = \beta_0 + \beta_v vol_{i,t} + \beta_z Z_{i,t} + \beta_r rf_t + a_i + u_{i,t} \qquad \textit{Equation 9}$$

$$S_{i,t} = \beta_0 + \beta_v vol_{i,t} + \beta_q lev_{i,t} + +\beta_r rf_t + a_i + u_{i,t}$$

Equation 9[22] illustrates the risk of heterogeneity bias by separating the composite error, $\varepsilon_{i,t}$, into two components, $a_i + u_{i,t}$. The a_i represents the component of the composite error which is not time-changing, whereas the $u_{i,t}$ represents the component that changes with time. An example of a non-changing unobservable could be the market view that management in a certain corporation is very poor which might affect the CDS spread. This view may persist during the sample period. The existence of such constant effects which are not captured in the model creates the implicit assumption that they are not correlated to any of the explanatory variables. Such correlation would create a heterogeneity bias which is really nothing more than an omitted variable bias. Nevertheless, the pooled cross section regression in *Equation 9* was estimated although the focus of this paper is on other estimation methods.

[21] This could be avoided using dummy variables, but this approach is not suitable as we have relatively few data points for each time period.
[22] The regression equations are presented in pairs to illustrate the comparison between leverage and Altman's Z.

3.3.2 The fixed effects model

The heterogeneity bias can easily be avoided by adopting a fixed effects[23] model. The fixed effects transformation, or within transformation, allows the unobserved, time-constant effects to be correlated to the included explanatory variables by studying the variation instead of the levels of the data. The transformation of the data is achieved by subtracting the average values of the parameters in the expression from the original expression. In *Equation 10,* the line above the letters indicate the sample average.

$$\overline{S}_{i,t} = \beta_0 + \beta_v \overline{vol}_{i,t} + \beta_z \overline{Z}_{i,t} + \beta_r \overline{rf}_t + \overline{a}_i + \overline{u}_{i,t} \qquad \textit{Equation 10}$$

$$\overline{S}_{i,t} = \beta_0 + \beta_q \overline{lev}_{i,t} + \beta_v \overline{vol}_{i,t} + \beta_r \overline{rf}_t + \overline{a}_i + \overline{u}_{i,t}$$

By subtracting *Equation 10* from *Equation 9*, we obtain *Equation 11,*

$$S_{i,t} - \overline{S}_{i,t} = \beta_v vol_{i,t} - \beta_v \overline{vol_{i,t}} + \beta_z Z_{i,t} - \beta_z \overline{Z}_{i,t} + \beta_r rf_t - \beta_r \overline{rf}_t + u_{i,t} - \overline{u}_{i,t} \qquad \textit{Equation 11}$$

$$S_{i,t} - \overline{S}_{i,t} = \beta_q lev_{i,t} - \beta_q \overline{lev}_{i,t} + \beta_v vol_{i,t} - \beta_v \overline{vol_{i,t}} + \beta_r rf_t - \beta_r \overline{rf}_t + u_{i,t} - \overline{u}_{i,t}$$

where the time-constant error and the intercept disappear from the equation. This can be rewritten as in *Equation 12.*

$$\overline{\overline{S}}_{i,t} = \beta + \beta_v \overline{\overline{vol}}_{i,t} + \beta_z \overline{\overline{Z}}_{i,t} + \beta_r \overline{\overline{rf}}_t + \overline{\overline{u}}_{i,t} \qquad \textit{Equation 12}$$

$$\overline{\overline{S}}_{i,t} = \beta_q \overline{\overline{lev}}_{i,t} + \beta_v \overline{\overline{vol}}_{i,t} + \beta_r \overline{\overline{rf}}_t + \overline{\overline{u}}_{i,t}$$

[23] Specification of terms: This paper will refer to the within transformation as a fixed effects model and the first difference model as a first difference model although some people would refer to both methods as variations of the fixed effects approach.

The new variables in *Equation 12* are said to be time-demeaned and include only the deviations of the observations from their sample mean. Hence, the fixed effects estimation in *Equation 12* is not affected by any time-constant unobservables. Instead, it is very similar to a first-differenced equation in that it measures how much the CDS spread changes when one of the explanatory variables changes. The drawbacks with the fixed effects model are that we lose the intercept and also the effect of any individually non-changing explanatory variables. The only case where this might be a problem would be for the Z-score which differs more between firms than within firms over time. Because these firm-specific differences are not included in the model, the explanatory power of the Z-score may be underestimated in a fixed-effects model. This is treated further in the discussion of the results. Note that the variables are calculated as deviations from the mean of the individual firms.

The raw data is recorded from 30 firms during 12 quarters. This gives 360 individual data points. Because the levels of the CDS price differs a great deal between different firms according to initial credit risks, it may be more interesting to view the *percentage* changes in the CDS spreads. We therefore add another regression: *Equation 13*, which measures the *percentage* deviations from the mean. This is done by performing the steps in *Equation 10* to *Equation 12* again, this time using the logarithm of the CDS spread as dependent variable.

$$\overline{\overline{\ln(S_{i,t})}} = \beta_v \overline{\overline{vol_{i,t}}} + \beta_z \overline{\overline{Z_{i,t}}} + \beta_r \overline{\overline{rf_t}} + \overline{\overline{u_{i,t}}} \qquad \textit{Equation 13}$$

$$\overline{\overline{\ln(S_{i,t})}} = \beta_q \overline{\overline{lev_{i,t}}} + \beta_v \overline{\overline{vol_{i,t}}} + \beta_r \overline{\overline{rf_t}} + \overline{\overline{u_{i,t}}}$$

As noted in earlier research, the explanatory power of differenced regressions is generally lower than that of level regressions[24]. They may therefore provide more rigorous test of the theory. An alternative approach would be to run time series regressions for each of the 30 firms individually and calculate the average coefficients from the regressions. The problem with this approach is that it would result in very few observations for each regression and therefore create unreliable estimates.

3.3.3 Regression with first differences

In addition to the fixed effects model, a one-step differenced regression was created. The expression for this model is illustrated in *Equation 14.*This method also eliminates the heterogeneity bias but runs the risk of moving average correlation in the residuals. Another drawback is that it eliminates 30 data points in our sample, reducing the test to 330 observations. This method should indicate the same effects as the fixed effects model, and the reason for including it along with the fixed effects model is partly that it may have a more practical interpretation of achieved coefficients. However the main reason is to facilitate the possibility of direct comparison to earlier studies using differenced regressions.

$$\Delta S_{i,t} = \beta_v \Delta vol_{i,t} + \beta_z \Delta Z_{i,t} + \beta_r \Delta rf_t + \Delta u_t \qquad \textit{Equation 14}$$

$$\Delta S_{i,t} = \beta_q \Delta lev_{i,t} + \beta_v \Delta vol_{i,t} + \beta_r \Delta rf_t + \Delta u_t$$

[24] For an example of this, see Ericsson et al (2004)

4. Data

The data section concerns the raw data used in the study. The source, format and range are specified and discussed for each data set.

4.1 Reference Entities

Because we are studying CDS premia, it is meaningful to say something about the how the reference entities were chosen. The initial selection was made to achieve a global mix of sectors and nationalities of some of the largest companies in the world. The main reason for choosing large companies was to make sure that data would be available. Naturally, this also leads to a bias towards companies with higher credit ratings. One might suspect that companies with worse ratings react differently to changes in the explanatory variables. However, the sign of the coefficients should be the same regardless of credit rating. The effects should also be statistically significant for all firms. The reason for choosing different sectors and countries was to be able to draw general conclusions about CDS spreads. Unfortunately, differing accounting standards and availability of data reduced the sample to mostly U.S. and a few European companies. We were also forced to exclude a few firms such as banks and insurance companies as they are not compatible with the Altman's Z explanatory variable. Despite these adjustments in the selection process, the goal is for the resulting regression to be quite general and applicable to the CDS prices of most firms. This is a realistic notion as long as the above restrictions are kept in mind.

4.2 CDS premia

The CDS prices were found as daily data from the Datastream database. The history dates back to the beginning of 2003, giving us about three years of quotes and making the CDS spreads the limiting factor to the study in terms of time span. The data is taken as the mid price at closing each day and is quoted in basis points. All of the CDS contracts are for five-year protection on senior debt as it is the most traded contract type. For example, a quote of 100 basis points means that the price of insurance is one percent of the notional amount, usually paid quarterly. The standard day-count measure for CDS agreements is A/360. *Figure 6* illustrates the CDS prices quoted in the study. There are a few extreme values which may have reduced the explanatory power of the study somewhat. However, no adjustment was made to the data.

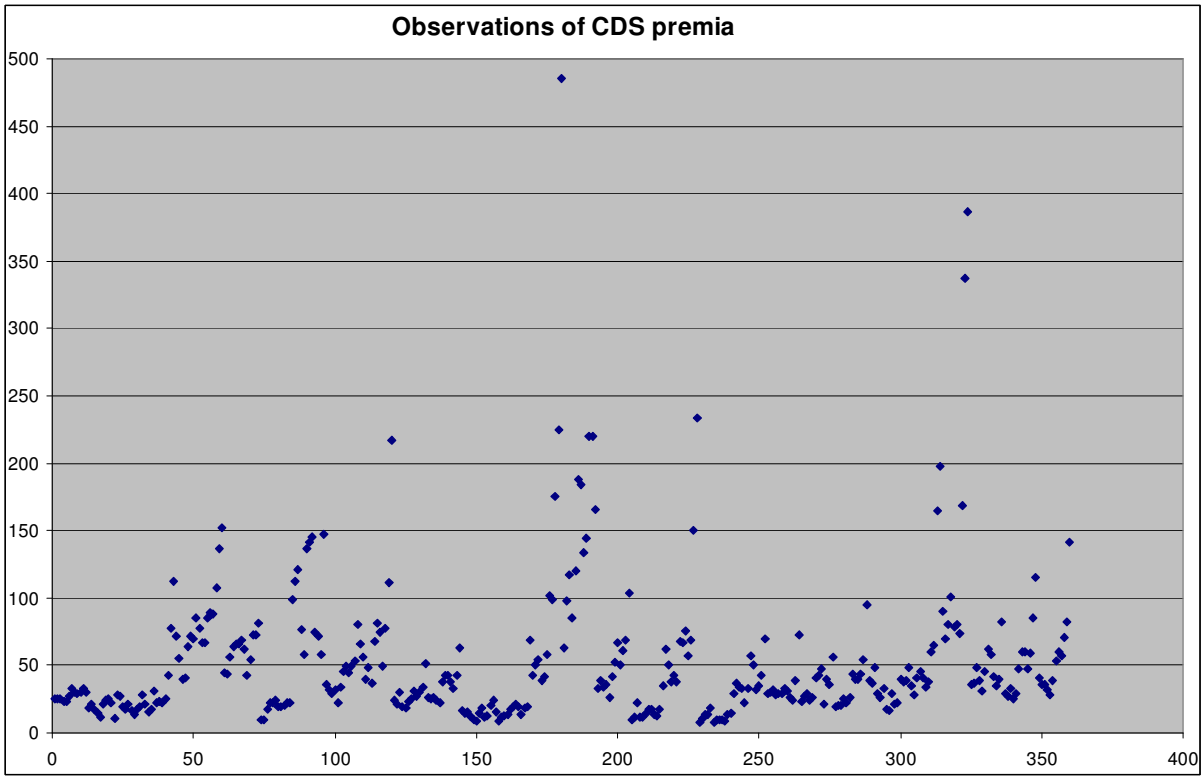

Figure 6: Representation of the CDS prices used in the study. The data consists of 360 observations spread out on 30 corporations between 2003-01-01 and 2005-12-31.

4.3 Risk-free rate

As stated above, the rate used to represent the risk-free rate is the five year interest rate swap spread minus ten basis points. The rate was obtained from Datastream and represents the mid price at close[25]. The data could be obtained daily, but the regression only requires quarterly rates. The study separated European and U.S. firms in terms of risk free rate and selected the appropriate swap rate depending on the geographic position of the firm.

4.4 Volatility

The measure of volatility was calculated from daily equity closing prices obtained via Datastream. The volatility is calculated as the standard deviation of stock-returns during the last quarter. This is in accordance with *Equation 6* above. The calculations are made so that the dates included are in accordance with the time since the last quarterly report for each firm.

4.5 Altman's Z-score

The data needed to calculate Altman's Z-score is available four times per year from Reuters and Datastream. Because quarterly measurement gives comparably few data points, firms with less than quarterly reports were excluded from the sample and replaced by others. This approach creates 30 times four data points per year for three years, giving a total of 360 data points. The data for *total current assets, current liabilities, total assets, operating result, total liabilities and revenue* were obtained from Reuters. All of these are reported quarterly and recorded in the local currency. *Retained earnings* was acquired from Datastream and is defined by Altman as the total nominal sum of retained earnings in the history of the firm. *Total market cap* was also acquired via Datastream and represents the share price times the number of shares outstanding. The Z-score is then calculated according to *Equation 7* in section 3.

[25] The mid price refers to the average of the bid and ask price.

4.6 Data matching

The data in the sample is matched according to the dates of the quarterly reports. If a report is released on the 31st of December, the CDS spread and risk-free rate are taken as the closing quotes of that day or the closest following day where a quote is available. The volatility is calculated from the daily stock returns since the last report and up to the current. The Z-score and leverage are calculated from the numbers presented in the report on that same day.

5. Results

This section will start by presenting the summary statistics of the CDS data and the explanatory variables. This is followed by key results of the performed regressions along with short explanations.

5.1 Key statistics and regression results

The full regression output is placed in the appendix. However, the *Regression Summary* below provides an overview of the results. *Tables 2* and *3* in the appendix present summary statistics of the different variables employed in the regressions. We can see from *Table 2* that the difference between the highest and lowest observation of CDS is around 525 basis points. This is a very large difference compared to the 5,3 basis points between the maximum and minimum individual deviation from the mean in *Table 3*. Similar observations can be made for all firm-specific variables. This illustrates the loss of variation inherent in the fixed effects method.

The first regression performed[26] was the fixed effects model specified in *Equation 12*[27], the results are presented in *Tables 4 and 5.* As we can see from *Table 4*, all of the coefficients display the expected sign along with a high level of significance. This confirms the basic hypothesis that Altman's Z-score is inversely correlated to the CDS price of a firm. It also confirms earlier research on the effect of volatility and the risk free rate. The three factors combined explain about a third of the variation in the CDS price.

[26] All regressions are performed using OLS and the Eviews 4 software.
[27] For quick reference to all the regression results, see the *Regression Summary* below.

Table # in appendix	Dependent Variable	Explanatory Variable	Coefficient	T-stat	R-squared of regression
Fixed Effects Model					
4	CDS, distance from mean	Volatility	33,97503	9,109415	**31,66%**
		Risk Free Rate	-6,757889	-2,417556	
		Altman's Z	-14.70174	-4.357318	
5	"	Volatility	27.66095	7.965071	**43,35%**
		Risk Free Rate	0.599408	0.228119	
		Leverage	4.029940	9.824837	
6	CDS, percentage distance from mean	Volatility	43.23010	10.32875	**41,72%**
		Risk Free Rate	-12.62711	-4.025319	
		Altman's Z	-23.58420	-6.228774	
7	"	Volatility	35.78464	9.181644	**51,68%**
		Risk Free Rate	-3.141622	-1.065352	
		Leverage	5.050240	10.97084	
8	"	Risk Free Rate	-27.42389	-8.293810	**16,08%**
9	"	Volatility	52.51571	13.36308	**33,22%**
10	"	Altman's Z	-25.77219	-5.441598	**7,62%**
11	"	Leverage	6.849639	14.48723	**36,89%**
One-step Differenced Model					
12	CDS-CDS(-1)	Volatility	24.96421	7.356008	**11,39%**
		Risk Free Rate	-0.193608	-0.073010	
		Altman's Z	-3.572131	-1.148429	
13	"	Altman's Z	-6.712035	-2.023224	**3,39%**
14	"	Volatility	20.41442	6.197900	**20,27%**
		Risk Free Rate	-0.212938	-0.084668	
		Leverage	2.876288	6.155277	
Level Regressions					
15	CDS	Altman's Z	-6.204084	-4.839888	**6,14%**
		Constant	66.56379	16.52352	
16	"	Leverage	0.557863	4.348380	**5,02%**
		Constant	30.04495	5.278860	
17	"	Volatility	43.74737	10.84688	**34,46%**
		Risk Free Rate	-4.297312	-1.150179	
		Altman's Z	-7.625669	-6.983836	
		Constant	20.31865	1.179650	

Regression summary: Each regression is provided in full in the appendix.

Table 5 replaces Altman's Z with leverage and performs the same regression. This produces some interesting effects. We first notice that the leverage is highly significant with the expected sign. The importance of volatility is largely unchanged, but the risk free rate has lost all significance. The reason for this loss of significance may be serial correlation in the sample. Analysis shows that the loss of significance only occurs when leverage is included in the regressions.

When calculating the correlation between the leverage and the risk free rate in the sample we get a correlation of -0,39. Also, a regression trying to explain leverage with the risk free rate or vice versa yields highly significant coefficients. Note that this is still performed within the fixed effects framework. The result that higher interest rates would lead to lower leverage in firms has not been discussed in earlier papers performing empirical components analysis. This paper notes that there may well be an economic negative relationship between leverage and the risk free rate as the present value of debt would decrease with higher interest rates. However, not further action is taken to investigate the matter and it is left for future research.

Continuing the analysis of *Table 5*, we see that the R-squared is about ten percent higher when including leverage. Hence, leverage appears to be more suited for explaining variations in the CDS spread. This is seen more clearly in *Tables 10* and *11* where the individual variables are regressed separately against the percentage deviation of CDS from its mean.

Tables 6 and *7* proceed by exchanging the deviation of CDS from its mean by the *percentage* deviation. This is done because the levels of differ greatly between firms, and a deviation of e.g. five basis points matter relatively more for firms with lower spreads. As expected, the coefficient values increase in absolute size compared to *Table 4*. Once again we see the expected signs and even higher levels of significance, notably for the risk free rate. Also, the transformation succeeded in increasing the explanatory power of the regression to 41 percent. The results of *Table 7* are also as expected. Higher significance compared to *Table 7* and *Table 8* indicates the better fit with percentage changes in CDS. The tables also confirm that leverage has a higher explanatory power compared to the Z-score.

Tables 8 to 11 illustrate the output from regressing the *individual* explanatory variables on percentage deviations of CDS. The results from the same regressions on the CDS mean are not included but yield similar output, only with lower explanatory power. *Table 8* illustrates more clearly the negative individual effect of the risk free rate on CDS prices[28]. We can also see that it has an individually high explanatory power and significance. The reason for the low significance in combination with other variables may be as suggested earlier, the presence of serial correlation, perhaps due to exogenous variables. From *Table 9* we can see that the individual regression confirms the effect of volatility and indicates a high explanatory power. In comparing *Tables 10* and *11*, the effects and significances of both leverage and Altman's Z-score are confirmed. However, the explanatory power of leverage is about 37 percent whereas Altman only reaches seven percent. This once again speaks in favour of leverage as a better indicator of CDS changes.

[28] This negative bias is documented by Longstaff and Schwartz (1995), Duffee (1998) and Ericsson (2004)

The next step is the difference regressions illustrated in tables *(34)* and *(36)*. These regressions confirm the high significance of volatility and leverage but once again show an insignificant coefficient for the risk free rate. Also, one notes that Altman's Z-score is insignificant in *Table 12.* The explanatory power of the included variables is lower in general and the highest R-squared reached is 20 percent which is to be compared to above 50 percent in the fixed effects model. The reason for the lower significance is that the difference method of analyzing data places higher demands on the comovement of variables. The insignificance of Altman's Z is probably to a further decrease in variation in the difference sample. *Table 13* illustrates that the Z-score is still significant when regressed on its own.

Tables 15, 16 and *17* are interesting to study as they show the result of regressing the variables leverage and Altman's Z on the *levels* of CDS prices. This means that the ability to explain inter-firm differences is included in the regression. Both variables are still significant, but we can see that all of a sudden the Z-score has almost twice the explanatory power of the leverage variable. This indicates that the Z-score may be a bit too blunt to accurately explain the smaller changes in a firm over time, but has abetter ability to see the big picture and compare different firms. *Table 17* shows the earlier variables in a simple pooled cross-section on the CDS prices. The explanatory power is quite low[29] and once again, the coefficient for the risk free rate is insignificant.

[29] Ericsson et al (2004) reached an R-squared of around 60 percent for level regressions.

5.1.1 Summary of regression results

The fixed effect regressions performed displayed explanatory levels of between 40 and 50 percent. The signs and significance for leverage, volatility and Altman's Z-score were as expected and confirmed earlier research. The explanatory power of Altman's Z, however, was lower than that of leverage. This may be due to the fact that the variation in the Z-score is mainly between different firms and not so much over time within a firm. The risk free rate of return was significant and had the predicted negative effect on CDS spreads in the regression with the Z-score and volatility. When including the leverage, however, the risk free rate became insignificant. This may be an indication of serial correlation in the variables. This is an unexpected result as there has been no indication of similar results in earlier research on empirical components. One reason for this may be the fact that we in practice only have much fewer observations of the risk free rate compared to the other variables.

The risk free rate is measured on each report date for the different firms. And since most firms report their quarterly figures on the same standard dates, the observations will be the same. This could in turn lead to unwanted effects such as too little variation in the variable, resulting in insignificant coefficients. This paper leaves a more thorough investigation into this matter to future research and concludes that it cannot fully confirm the earlier results on risk free rate.

The differenced regressions produced similar results to the fixed effects model but with lower overall significances. This was expected and is due to the structural differences in the models. What is notable, however, is that Altman lost its statistical significance. This is another indication that Altman is more appropriate for inter-firm level explanation. The level regression also suffers from low levels of significance. The main finding, however is that it switches the order of importance of leverage and Altman's Z. In the level regressions, where inter-firm differences are included, the Z-score has a significantly higher explanatory power compared to the leverage variable.

6. Discussion

This section will discuss the regression data presented in the last section and link the results to existing theory. In order to give the reader a better overview, the discussion is separated into one section per variable. Apart from discussing the results, weaknesses of the study are brought up along with suggestions of improvements and further research.

6.1 Risk free rate

This variable was expected to follow the results of Longstaff and Schwartz (1995), CGM (2001), Benkert (2004) and Ericsson et al (2004) in having a significant negative effect on the CDS price. The reasons for this effect have been discussed, but the main argument seems to be that a higher risk-free rate decreases the risk of default when one models the geometric Brownian drift of a firm. Also, because we view the CDS price as the price of a put option on the firm, it is natural that a higher risk-free rate should lead to a decrease in the CDS price. Nevertheless, the results were not strictly in accordance with theory. In the regressions where the variable was significant, it indeed had a negative coefficient. On the other hand, several of the tests performed rendered the risk free rate insignificant to the price of a CDS. More specifically, the significance was lost in the fixed effects regression when Altman's Z-score was substituted for leverage. This is an interesting result as it suggests the possibility of serial correlation between the leverage and risk free rate. Also, a simple regression of leverage on risk free interest rate yields a highly significant negative coefficient in the sample used. Such correlation is intuitively plausible if one considers the value of a firm's liabilities to be negatively correlated to the discount rate.

Also, one might consider the fact that companies will increase their leverage during times when credit is cheap. Another explanation would be that the relatively few observations of risk free rate in the sample[30] have led to a random covariation with the leverage of the included firms. In any case, the significance of the risk free rate is weak and this study cannot unconditionally support the results of earlier research. However, the significant results achieved appear to confirm earlier results. The apparent correlation between the risk free rate and leverage is left for future research.

6.2 Volatility

Earlier empirical components research and the structural models all agree that the coefficient for volatility should be positive[31]. The reason for this is intuitive as increased volatility increases the risk of default and also the price of a put option. The regressions of historical equity volatility all confirm this result and thereby also earlier studies.

6.3 Altman's Z-score

The Z-score is a combination of different financial ratios which has the purpose of predicting whether or not a company is risking default. The higher the value of Altman's Z-score, the better the health of the company. Therefore, Altman's Z was predicted to have a negative coefficient. The hypothesis also stated that the Z-score would have a higher explanatory power than the leverage of a firm because it takes into account other ratios as well. The Z-score turned out to be a highly significant estimator with the predicted sign. However, in terms of explanatory power, it was outperformed by leverage in all of the regressions measuring differences within a firm over time[32]. This may be either because leverage is better at predicting default

[30] The sample contains twelve data points per firm, each on a quarterly report date. Because many firms report on the same date and the others on nearby dates, similar risk free rates are repeated in the sample.
[31] See CGM (2001), Campbell and Taksler (2003), Cremers et al (2004), Benkert (2004) and Ericsson et al (2004)
[32] Note that the fixed effects model and the difference model measures differences within firms over time whereas the level regression also includes differences between firms.

risk or because the differences in firms over time were too small to be reflected significantly in the Z-score. The latter explanation seems more plausible in light of the fact that the Z-score dominated the leverage variable in terms of explanatory power in the level regressions.

6.4 Leverage

Earlier research on empirical components[33] has noted leverage as one of the three most significant variables extracted from the structural models to be used in the empirical components approach. The leverage of a firm basically denotes the ratio of debt to assets of a firm and should have a positive correlation with the CDS price. As with volatility, the results are significant in all cases and we can confirm our predictions in all regressions. The only thing worth commenting is once more the substitutability with Altman's Z. When the two variables appear in the same regression, one becomes insignificant and there is obviously a correlation between them. This study indicates that leverage is more important in explaining intra-firm changes over time, whereas the Z-score is better at explaining level differences between firms.

[33] See references for the risk free rate.

6.5 Weaknesses and possible future research

The general level of explanatory power in the regressions was low compared to earlier studies. This is likely to be the result of using fewer data points and not interpolating the data. However, an interesting task for future research would be to conduct principal components analysis of the residual series in order to possibly identify additional explanatory variables[34]. Another subject of future study might be the correlation of interest rates and leverage to see whether the problem experienced in this study was a coincidence or something to be regarded during model-building. Given that this study has indeed moved away from strictly structural-model-based variables by including the Z-score, there is no reason to stop there. Future studies could attempt to find other significant variables which may not be substitutes, but complements to existing ones[35].

[34] This was attempted by Ericsson et al (2004) without identifying any additional variables for their series.
[35] CGM (2001) found a high level of negative significance when using the S&P 500 index as an explanatory variable. The explanation suggested was that the stock index is a proxy of general economic conditions which would have a negative correlation to CDS spreads.

7. Conclusion

This section will provide a summary of the results achieved in this paper and conclude the study.

This paper set out with two aims. The first was to confirm earlier research on the effect of certain empirical components on a new data set. The second was to test the hypothesis that Altman's Z-score is superior to leverage in explaining CDS prices. The paper also provided a background of the credit derivatives markets and of the research leading up to the empirical components approach. The results were a partial achievement of the goals set out. Earlier results using the empirical components approach were confirmed albeit with a question mark regarding the risk free rate. The hypothesis regarding the Z-score was also put into question. Although the variable had a statistically and economically significant effect on the price changes of the CDS in our main regressions, the leverage still had a higher explanatory power. This was in essence a rejection of the hypothesis of this paper. However, in the level regressions conducted at the end, the hierarchy changed with the Z-score showing almost twice the level of explanatory power to that of leverage. This is likely to be due to the fact that the pooled cross sectional regression includes the inter-firm differences. The Z-score may be weaker in picking up small changes within a firm over time, but stronger at comparing different firms. One of the subjects suggested for further research may therefore be to continue the analysis with Altman's Z as an explanatory variable and also to include new previously untested variables to increase the explanatory power of the test. Another matter worth another mention is the seemingly negative relationship between the risk free rate and leverage. If the relationship is strong enough to affect the inference in similar ECA studies, it may well be worth future research.

Appendix

A. Summary statistics

	CDS	ALTMAN	RISKFREE	VOL	LEV
Mean	56.38199	2.423303	3.735493	0.016013	38.68462
Median	37.62130	1.781306	3.716500	0.013942	36.64613
Maximum	532.5000	11.75962	4.915000	0.045033	91.43010
Minimum	7.500000	-1.802600	2.277500	0.005593	5.637170
Std. Dev.	63.82412	2.111046	0.654278	0.007103	20.81080
Sum	20297.52	872.3889	1344.777	5.764531	13926.46
Sum Sq. Dev.	1462393.	1599.889	153.6806	0.018113	155479.1
Observations	360	360	360	360	360

Table 2: Summary statistics of the variables used in the regressions.

	ALTMAN	CDS	LEVERAGE	PERCCDS	VOL	RISKFREE
Mean	-1.57E-16	-1.03E-15	-1.18E-15	-2.21E-15	5.18E-17	2.96E-16
Median	-0.012229	-2.568066	-0.096675	-8.597440	-0.094313	0.028771
Maximum	2.998871	364.9715	20.94600	304.0706	1.985641	1.014625
Minimum	-2.356810	-82.36961	-11.41347	-67.71452	-1.476910	-1.495458
Std. Dev.	0.476292	36.59455	3.943330	44.46883	0.488039	0.648777
Sum	-6.05E-14	-4.26E-13	-3.20E-13	-4.83E-13	1.87E-14	1.31E-13
Sum Sq. Dev.	81.44065	480758.8	5582.397	709914.3	85.50749	151.1073
Observations	360	360	360	360	360	360

Table 3: Summary statistics of deviation from mean

B. Regression output and diagrams

B.1 Fixed effects model

Dependent Variable: CDS
Method: Least Squares
Date: 06/12/06 Time: 17:58
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VOL	33.97503	3.729661	9.109415	0.0000
RISKFREE	-6.757889	2.795340	-2.417556	0.0161
ALTMAN	-14.70174	3.374034	-4.357318	0.0000
R-squared	0.316639	Mean dependent var		-1.03E-15
Adjusted R-squared	0.312811	S.D. dependent var		36.59455
S.E. of regression	30.33573	Akaike info criterion		9.670828
Sum squared resid	328531.7	Schwarz criterion		9.703212
Log likelihood	-1737.749	Durbin-Watson stat		1.309386

Table 4: Regression output

Dependent Variable: CDS
Method: Least Squares
Date: 06/12/06 Time: 17:59
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RISKFREE	0.599408	2.627617	0.228119	0.8197
VOL	27.66095	3.472782	7.965071	0.0000
LEVERAGE	4.029940	0.410179	9.824837	0.0000
R-squared	0.433476	Mean dependent var		-1.03E-15
Adjusted R-squared	0.430302	S.D. dependent var		36.59455
S.E. of regression	27.62096	Akaike info criterion		9.483325
Sum squared resid	272361.4	Schwarz criterion		9.515709
Log likelihood	-1703.999	Durbin-Watson stat		1.243299

Table 5: Regression output

Dependent Variable: PERCCDS
Method: Least Squares
Date: 06/12/06 Time: 18:01
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VOL	43.23010	4.185414	10.32875	0.0000
RISKFREE	-12.62711	3.136922	-4.025319	0.0001
ALTMAN	-23.58420	3.786331	-6.228774	0.0000
R-squared	0.417213	Mean dependent var		-2.21E-15
Adjusted R-squared	0.413949	S.D. dependent var		44.46883
S.E. of regression	34.04267	Akaike info criterion		9.901405
Sum squared resid	413728.5	Schwarz criterion		9.933789
Log likelihood	-1779.253	Durbin-Watson stat		1.653710

Table 6: Regression output

Dependent Variable: PERCCDS
Method: Least Squares
Date: 06/12/06 Time: 18:03
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VOL	35.78464	3.897411	9.181644	0.0000
RISKFREE	-3.141622	2.948906	-1.065352	0.2874
LEVERAGE	5.050240	0.460333	10.97084	0.0000
R-squared	0.516789	Mean dependent var		-2.21E-15
Adjusted R-squared	0.514081	S.D. dependent var		44.46883
S.E. of regression	30.99827	Akaike info criterion		9.714038
Sum squared resid	343038.7	Schwarz criterion		9.746423
Log likelihood	-1745.527	Durbin-Watson stat		1.666335

Table 7: Regression output

Dependent Variable: PERCCDS
Method: Least Squares
Date: 06/12/06 Time: 18:04
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RISKFREE	-27.42389	3.306549	-8.293810	0.0000
R-squared	0.160798	Mean dependent var		-2.21E-15
Adjusted R-squared	0.160798	S.D. dependent var		44.46883
S.E. of regression	40.73700	Akaike info criterion		10.25492
Sum squared resid	595761.6	Schwarz criterion		10.26572
Log likelihood	-1844.886	Durbin-Watson stat		1.448189

Table 8: Regression output

Dependent Variable: PERCCDS
Method: Least Squares
Date: 06/12/06 Time: 18:05
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VOL	52.51571	3.929910	13.36308	0.0000
R-squared	0.332182	Mean dependent var		-2.21E-15
Adjusted R-squared	0.332182	S.D. dependent var		44.46883
S.E. of regression	36.33998	Akaike info criterion		10.02649
Sum squared resid	474093.3	Schwarz criterion		10.03728
Log likelihood	-1803.768	Durbin-Watson stat		1.527134

Table 9: Regression output

Dependent Variable: PERCCDS
Method: Least Squares
Date: 06/01/06 Time: 17:39
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALTMAN	-25.77219	4.736143	-5.441598	0.0000
R-squared	0.076197	Mean dependent var		-2.21E-15
Adjusted R-squared	0.076197	S.D. dependent var		44.46883
S.E. of regression	42.74107	Akaike info criterion		10.35097
Sum squared resid	655821.0	Schwarz criterion		10.36177
Log likelihood	-1862.175	Durbin-Watson stat		1.445455

Table 10: Regression output

Dependent Variable: PERCCDS
Method: Least Squares
Date: 06/01/06 Time: 17:39
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEVERAGE	6.849639	0.472805	14.48723	0.0000
R-squared	0.368935	Mean dependent var		-2.21E-15
Adjusted R-squared	0.368935	S.D. dependent var		44.46883
S.E. of regression	35.32586	Akaike info criterion		9.969881
Sum squared resid	448001.9	Schwarz criterion		9.980676
Log likelihood	-1793.579	Durbin-Watson stat		1.471768

Table 11: Regression output

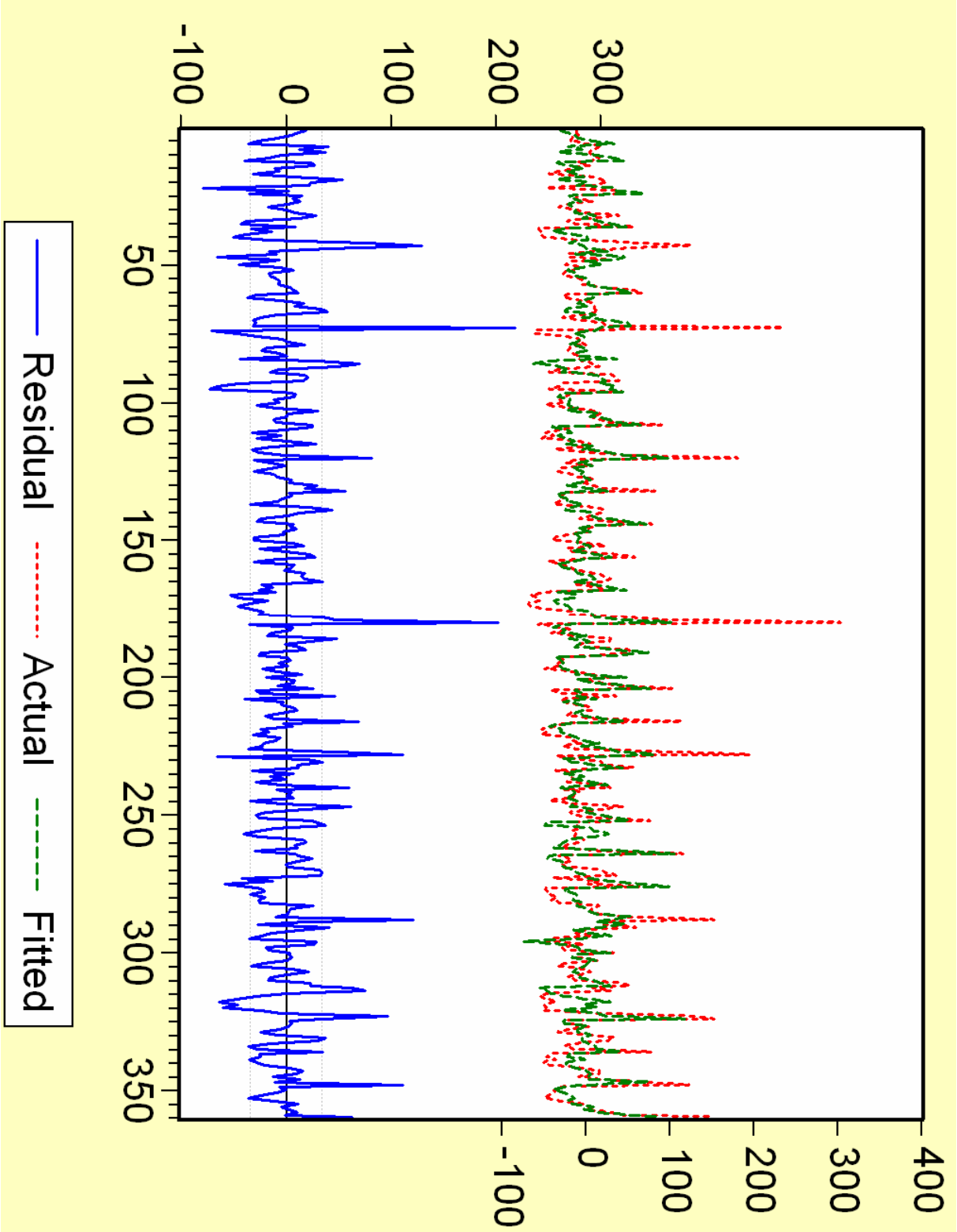

Figure 7: Actual, fitted and residual graph from Table 6.

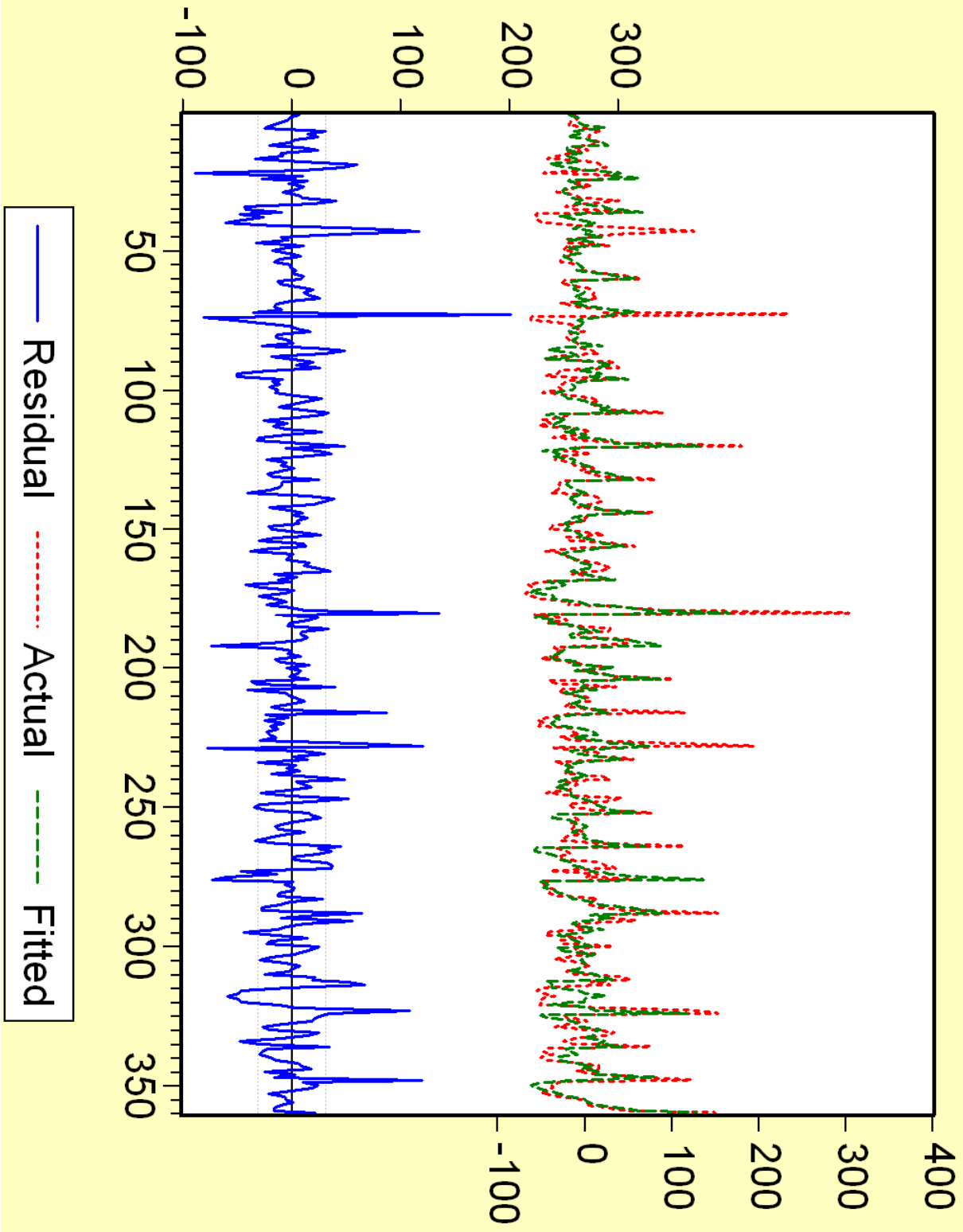

Figure 8: Actual, fitted and residual graph from Table 7.

B.2 Regressions from the one-step differenced model

Dependent Variable: CDS
Method: Least Squares
Date: 06/12/06 Time: 17:22
Sample: 1 330
Included observations: 330

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RF	-0.193608	2.651802	-0.073010	0.9418
VOLA	24.96421	3.393717	7.356008	0.0000
ALTMAN	-3.572131	3.110449	-1.148429	0.2516
R-squared	0.113881	Mean dependent var		5.778395
Adjusted R-squared	0.108462	S.D. dependent var		26.74839
S.E. of regression	25.25618	Akaike info criterion		9.305068
Sum squared resid	208585.0	Schwarz criterion		9.339606
Log likelihood	-1532.336	Durbin-Watson stat		1.601394

Table 12: Regression output, differences

Dependent Variable: CDS
Method: Least Squares
Date: 06/12/06 Time: 17:25
Sample: 1 330
Included observations: 330

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALTMAN	-6.712035	3.317494	-2.023224	0.0439
R-squared	0.033945	Mean dependent var		5.778395
Adjusted R-squared	-0.033945	S.D. dependent var		26.74839
S.E. of regression	27.19860	Akaike info criterion		9.447234
Sum squared resid	243382.2	Schwarz criterion		9.458746
Log likelihood	-1557.794	Durbin-Watson stat		1.507012

Table 13: Regression output, differences

Dependent Variable: CDS
Method: Least Squares
Date: 06/12/06 Time: 17:26
Sample: 1 330
Included observations: 330

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEVERAGE	2.876288	0.467288	6.155277	0.0000
RF	-0.212938	2.514965	-0.084668	0.9326
VOLA	20.41442	3.293765	6.197900	0.0000
R-squared	0.202687	Mean dependent var		5.778395
Adjusted R-squared	0.197810	S.D. dependent var		26.74839
S.E. of regression	23.95721	Akaike info criterion		9.199465
Sum squared resid	187680.9	Schwarz criterion		9.234002
Log likelihood	-1514.912	Durbin-Watson stat		1.635229

Table 14: Regression output, differences

B.3 Level regression

Dependent Variable: CDS
Method: Least Squares
Date: 06/12/06 Time: 18:30
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALTMAN	-6.204084	1.281865	-4.839888	0.0000
C	66.56379	4.028426	16.52352	0.0000
R-squared	0.061413	Mean dependent var		51.89996
Adjusted R-squared	0.058791	S.D. dependent var		51.92301
S.E. of regression	50.37358	Akaike info criterion		10.68235
Sum squared resid	908424.0	Schwarz criterion		10.70394
Log likelihood	-1920.823	F-statistic		23.42452
Durbin-Watson stat	0.775906	Prob(F-statistic)		0.000002

Table 15: Regression output, levels

Dependent Variable: CDS
Method: Least Squares
Date: 06/12/06 Time: 18:31
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEVERAGE	0.557863	0.128292	4.348380	0.0000
C	30.04495	5.691560	5.278860	0.0000
R-squared	0.050167	Mean dependent var		51.89996
Adjusted R-squared	0.047514	S.D. dependent var		51.92301
S.E. of regression	50.67447	Akaike info criterion		10.69426
Sum squared resid	919308.8	Schwarz criterion		10.71585
Log likelihood	-1922.967	F-statistic		18.90840
Durbin-Watson stat	0.762161	Prob(F-statistic)		0.000018

Table 16: Regression output, levels

Dependent Variable: CDS
Method: Least Squares
Date: 06/12/06 Time: 18:33
Sample: 1 360
Included observations: 360

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALTMAN	-7.625669	1.091903	-6.983836	0.0000
RISKFREE	-4.297312	3.736210	-1.150179	0.2508
VOL	43.74737	403.3176	10.84688	0.0000
C	20.31865	17.22431	1.179650	0.2389
R-squared	0.344570	Mean dependent var		51.89996
Adjusted R-squared	0.339047	S.D. dependent var		51.92301
S.E. of regression	42.21291	Akaike info criterion		10.33438
Sum squared resid	634367.0	Schwarz criterion		10.37756
Log likelihood	-1856.188	F-statistic		62.38492
Durbin-Watson stat	0.774133	Prob(F-statistic)		0.000000

Table 17: Regression output, levels

C. List of reference entities

COCA-COLA ENTS. SEN 5YR CDS - CDS PREM. MID
PEPSI BOTTLING GROUP INC SEN 5YR CDS - CDS PREM. MID
UNITED TECHNOLOGIES CORP SEN 5YR CDS - CDS PREM. MID
WYETH SEN 5YR CDS - CDS PREM. MID
DAIMLERCHRYSLER AG SEN 5YR CDS - CDS PREM. MID
VOLKSWAGEN AG SEN 5YR CDS - CDS PREM. MID
DELL INC SEN 5YR CDS - CDS PREM. MID
SUN MICROSYSTEMS INC SEN 5YR CDS - CDS PREM. MID
VERIZON GLOBAL FDG. CORP SEN 5YR CDS – CDS PREM. MID
TIME WARNER INC SEN 5YR CDS - CDS PREM. MID
CONOCOPHILLIPS SEN 5YR CDS - CDS PREM. MID
BELLSOUTH CORP SEN 5YR CDS - CDS PREM. MID
CHEVRONTEXACO CAP.CO SEN 5YR CDS - CDS PREM. MID
ABBOTT LABORATORIES SEN 5YR CDS - CDS PREM. MID
TYCO INTERNATIONAL LTD SEN 5YRCDS - CDS PREM. MID
ALTRIA GROUP INC SEN 5YR CDS - CDS PREM. MID
WALT DISNEY SEN 5YR CDS - CDS PREM. MID
HOME DEPOT INC SEN 5YR CDS - CDS PREM. MID
COMCAST CORP SEN 5YR CDS - CDSPREM. MID
PFIZER INC SEN 5YR CDS - CDS PREM. MID
ALLTEL CORP SEN 5YR CDS - CDS PREM. MID
APPLIED MATS.INC. SEN 5YR CDS - CDS PREM. MID
BAXTER INTERNATIONAL INC SEN 5YR CDS - CDS PREM. MID
BOEING CO SEN 5YR CDS - CDS PREM. MID
BOSTON SCIEN.CORP SEN 5YR CDS - CDS PREM. MID
UNION PACIFIC CORP SEN 5YR CDS- CDS PREM. MID
AGILENT TECHNOLOGIES INC SEN 5YR CDS - CDS PREM. MID
CSX CORP SEN 5YR CDS - CDS PREM. MID
CARNIVAL CORP SEN 5YR CDS - CDS PREM. MID
DUKE ENERGY CORP SEN 5YR CDS - CDS PREM. MID

Table 18: The CDS quotes used in the study

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