The Pricing of Corporate Bonds and Determinants of Financial Structure

Håkan Thorsell

EFI THE ECONOMIC RESEARCH INSTITUTE

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PREFACE

The report is a result of a research project carried out at the Center for Financial Analysis and Managerial Economics in Accounting at the Economic Research Institute at the Stockholm School of Economics.

This volume is submitted as a doctor's thesis at the Stockholm School of Economics. The author has been entirely free to conduct and present the research in his own way as an expression of his own ideas, according to the normal practice of the Economic Research Institute.

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Director of the Economic Research Institute at the Stockholm school of Economics	Director of the Center for Financial Analysis and Managerial Economics in Accounting at the Stockholm School of Economics

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EFI, Box 6501, SE-113 83 Stockholm, Sweden • Website: www.hhs.se/efi/
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Stockholm, April 2008

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Part I

Introduction and Summary of Thesis

Introduction

This dissertation consists of three papers. All three papers are concerned with the financial risk of companies. The first two deal with the pricing of corporate bonds from a bankruptcy risk perspective, and the third focuses on companies' choice of capital structure. A corporate bond is a promise by a company to pay cash at future dates. The capital structure of a company is the mix of debt and equity used to finance the company's assets.

In the first two papers I extract parameters from corporate bond prices at which investors trade. These parameters help me to gain knowledge as to how investors in general value the risk and expected return from corporate bonds. I make a distinction throughout the dissertation between value and price. Value is the estimated value of an asset and price is the price set by investors when they trade the asset.

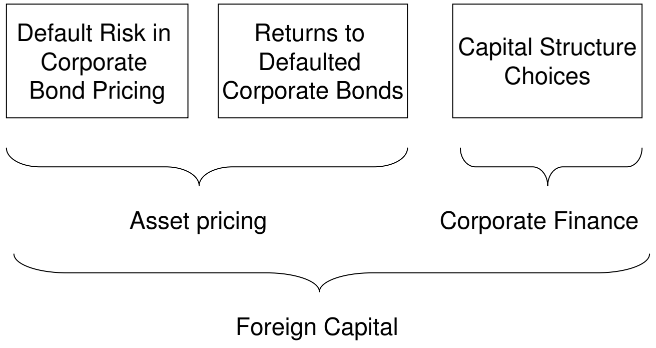
Both papers on corporate bonds are concerned with how investors estimate and price uncertain repayments. The first paper investigates if the default risk is something that investors are concerned with when they trade corporate bonds. It might seem a strange question since all valuation models for risky bonds include a default[1] event, see for instance Skogsvik (2006). If there are many traded assets the question is if default risk shows up in the risk premium for the capital cost of bonds. This is the underlying question in the first paper. In the second paper the returns on defaulted bonds are tested for abnormal returns. Is a distressed asset priced in the same way as other assets? This question is answered with a data set of corporate bonds, where the companies have defaulted on their debts. How to value distressed assets is a problem that recurs from time to time and if the downturn in 2007 in the U.S. mortgage market continues it can become acute again. The study is important, since if there are persistent excess returns then there are systematic transfers of wealth from the sellers of the defaulted bonds to the new owners.

In my third paper, I follow in the footsteps of Donaldson (1961) and an old tradition at the Stockholm School of Economics represented by for instance Johansson (1973), Bertmar & Molin (1977), and Johansson (1998). The underlying idea tested in the paper is that companies do not actively choose their financing (capital structure), but 'end up with' some allocation depending on their historical profitability. In the paper this idea of historical profitability is

[1] Default occurs when a company fails to perform a specific required duty. Specifically the company defaults on its bonds if it fails to pay interest or principal on the due date, or declares itself in bankruptcy, insolvency or reorganization. Bankruptcy is a legal proceeding in the United States, where a trustee of an insolvent debtor liquidates and distributes assets in an equitable manner amongst creditors and owners.

tested against other ideas of capital structure choice.

Figure 1 The relation between the three papers.



In the next section, I give a general background on the issues covered in the papers, introduce a few concepts, provide some critique of methods and data, and describe the ordering of the papers. After this, I describe the problems that the papers address, why the papers are motivated, and, finally, describe the results.

Background

The company's owners can decide on the capitalization of the company. The owners can choose to include outsiders in the financing of the company, by for instance issuing debt. In general, debt has the advantage that interest payments are tax deductible for the company, but dividends are not. For the creditor there is an advantage in that he can limit his monitoring of the company, since a company services its debt before the owners receive any dividends. The creditor can rely on owners servicing debt as long as the owners run the business in a rational manner. However, the creditors cannot relax too much since a financially distressed company often cannot service its obligations against its creditors.

Some companies are subject to unforeseen risks even if the owners are diligent in the operations. This is obviously a major concern for creditors. However, for a creditor with many credits, a specific credit might not be so important since its pay-off might only have a marginal impact on the creditor's portfolio pay-off. However, creditors, banks and others, spend a lot of effort on credit evaluation. I define the value of a credit (that pays no coupon over the holding period) in (1);

$$V_t = e^{-r_t} E\left[V_{t+1}\right]. \tag{1}$$

The equation states that the value of the credit (V_t) at time t equals the present value of the expected value of the credit at the end of the next time period (V_{t+1}), discounted at r_t. The expected future value depends on the possible outcomes and how likely they are.

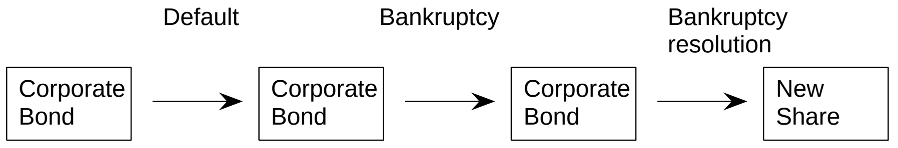
Let us form a portfolio (V^P) with a credits,

$$V_t^P = V_t^1 + ... + V_t^a = e^{-r_t} E[V_{t+1}^1 + ... + V_{t+1}^a]. \tag{2}$$

Note that the same discount rate has been assumed for all bonds in the portfolio. For simplicity I assume that each credit is of equal size. If a is large, each credit has a small impact on the portfolio distribution of pay-offs. It might not matter much for the investor if he does not get paid from one single credit. What the creditor needs to worry about is if several credits default at the same time. If the portfolio asset pay-offs co-vary and investors are risk averse, the investors typically require compensation in terms of higher expected return. My first essay studies the simultaneity of default risks. The value of any asset can be calculated from its future pay-off space. In terms of equation (1) this is done by the expectations operator ($E[\cdot]$). The promised payment falls in a later time period, so it should also be discounted. The discount factor should be such that it compensates for portfolio risks that are unavoidable (systematic risks). There are thus two ways the bankruptcy risk can influence bond values, through the adjustment to the expected payment and through the discount factor. The first adjustment depends on the individual bond's default risk and the second on whether the default risk is systematic or not.

Even after companies have defaulted, there might be some value to be extracted from their credits. It is rare that companies that default lose all their assets, so that creditors get no return on their debt assets. As defaulted bonds are assets, equation (1) must also apply to them. The pay-offs change if the company is not able to service the bond and the final pay-offs can be very different from what was promised. After default, the risk and return characteristics of a bond can be expected to be closer to a share. A typical transition process where a corporate bond becomes a new share is outlined in Figure 2. When the bond changes status, there might also be new reasons to trade it, and there might be other risks that influence the expected return. In my second paper, I investigate if there is any mispricing of defaulted bonds, so that for example buyers of recently defaulted bonds receive too much compensation in relation to the risks they bear.

Figure 2 Transition when a corporate bond becomes a share.



The prices of different sources of capital can have an impact on the choice of capital structure for the firm. There are a few established theories[2] on how companies choose between equity capital and borrowing (issuing corporate bonds, bank loans, etc). In my third paper I test two of them, the trade-off theory and the pecking order theory, and contrast them with a specific form of the pecking order ("historical chance"). The idea of the trade-off theory is that the owners of a company increase the level of debt as long as the benefits of more debt are larger than the costs. The trade-off theory is described in text books of corporate finance, for instance Brealey et al. (2006). The pecking order theory states that companies choose financing in order of its information sensitivity[3], in a pecking order. The pecking order theory has been found to align with actual company behavior in the United States by Shyam-Sunder & Myers (1999) and Lemmon & Zender (2002). Helwege & Liang (1996) and Frank & Goyal (2003) on the other hand find less support for a pecking order. The components of the pecking order can be grouped into asymmetric information based and profitability based (historical chance). The profitability based components align with the idea that the capital structure only to a lesser degree is an active choice, but rather that the empirical dispersion in capital

[2]A theory on capital structure is a logical structure that describes how firms choose their leverage. A theory is predictive, logical and testable. In contrast a hypothesis is a specific statement on application of the theory that needs evaluation. The mixed evidence on the capital structure theories raises the issue if they should be referred to as theories or merely hypotheses. I align with common practise in the literature and refer to them as theories.

[3]The concept of 'information sensitivity' relates to how much the price of the financing changes if investors think the company is a bad company. The price of debt changes little, unless the company is really poor, but the price of equity changes a lot. The problem is that there is asymmetric information, and the company cannot without cost reveal if it is a good or bad company.

structures is generated by profitability and sticky dividend policies. In other words, the capital structure is the outcome of the "historical chance" rather than an active choice.

Concepts

In this section I will elaborate on some theories and concepts that might be useful when reading the first two papers; the different classes of bond pricing models, the central concept in the Capital Asset Pricing Model (CAPM), and the credit spread puzzle.

Corporate bond pricing models have been divided into structural and reduced form models in for instance Uhrig-Homberg (2002), Duffie & Singleton (2003), and Lando (2004). The structural models are similar to option pricing models, but the underlying asset is not a share of owner's equity, but the assets of the company. Early papers using the structural approach are Black & Scholes (1973) and Merton (1974). Simplified, the equity owners have a call option on the assets of the company and they can choose to service the debt or default on the debt and hand over the company to the creditors. The mirror image of this is that the creditors can be considered to have issued a put option on the assets of the company, where the equity owners can sell them the assets for the face value of the debt. Bankruptcy occurs when the value of the assets goes below some prescribed limit (for instance the face value of debt), and the bankruptcy event is thus endogenous in structural models. Lando (2004) shows (chapter five) that the reduced form model can be viewed as a structural model with measurement error. Duffie & Singleton (1999) use the term "reduced form models" to describe an unpredictable default process. The default event is not directly dependent on company value, as for structural models.

A typical starting point for a reduced form model is a discounted cash flow (DCF) setting adjusted with a default rate process. The implementation of reduced form models is in general simpler than for structural models, since reduced form models do not require assessment of such parameters as market value and volatility of firm assets. However, even if the starting points of the two classes of models are different, they are not fundamentally different. The bond models used in this thesis belong to the reduced form models since they are not constructed as residual claims and the default event is exogenous. The choice of a reduced form model for the default process can influence the results. The distribution of bond returns in a reduced form setting can be limited by the bond's structural form and the exogenous default process can influence the estimates. On the first point, the structural form is most important when bonds are close to default, since it is then that the option-like character of the bond is important for returns. Only a small share of the bonds in the sample is ever close to default, so the impact of this potential problem should be small. The other potential problem from choosing a reduced form model is the exogenous default event. The exogenous nature of the default event means that the arrival intensity of default is not controlled in the model and thus the sample contains a random selection of defaults. Given that the arrival intensity is constant, a longer sample gives a better estimation of the distribution of the intensity.

In the first two papers the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), or the inter-temporal CAPM (ICAPM) of Merton (1973) is used to study the return from corporate bonds. The CAPM is compatible with any bond valuation model. The model used in my first two papers is based on the following equation;

$$E_t\left[m_{t+1}\mathbf{R}_{t+1}\right] = \mathbf{1}, \tag{3}$$

where m_{t+1} is the stochastic discount factor (SDF), $\mathbf{R}$ is the $(N \times t)$ vector of N assets gross returns[4], and $t+1$ is a time period subscript.

The existence of a m_{t+1} that satisfy equation (1.1) means that assets with the same payoffs have the same price. If m_{t+1} is restricted to be strictly positive it becomes a no-arbitrage condition. In equilibrium assets pricing models m_{t+1} has more structure. It is now defined as the intertemporal marginal rate of substitution, linking it to investor utility functions. A specification of the intertemporal marginal rate of substitution is the CAPM ($m_{t+1} = a + bR^W_{t+1}$), where a and b are free parameters and R^W_{t+1} is the return on the wealth portfolio. This is the specification used in the first two papers.

Bonds that have different risks have different yields[5], and the difference between a corporate bond yield and a government bond yield, with the same structure and maturity, is called a yield spread. There are many explanations for the existence of a yield spread, see for instance Duffee (1999), Elton et al. (2001), Ericsson & Reneby (2003), or Driessen (2005). The credit spread 'puzzle' is the empirical finding that observed historical default rates are not

[4]For each asset j the gross return is $R_{j,t+1} = \frac{P_{j,t+1}}{P_{j,t}}$ where $P_{j,t}$ is the price at time t.

[5]A yield is an interest rate. There are different yield concepts for bonds. Three common yield concepts are 1) coupon yield, 2) current yield and 3) yield-to-maturity. The coupon yield of a bond is defined as the coupon divided with the face value of the bond. The current yield is defined as the coupon divided with the current market price of the bond. The yield to maturity is the yield received by the bondholder if the bond is held to maturity. Coupon payments are assumed to be reinvested at the promised yield.

sufficiently high to motivate the size of the yield spread.

There can be other explanations to the credit spread puzzle, such as taxes, put/call conversion options, and systematically lower liquidity. If different bonds are taxed differently, more highly taxed bonds need a higher yield spread to generate the same return distribution to its investors. If the bond has options built in, these options have a value to the issuer or the investor depending on who has the rights. The flexibility that comes with these options has a value that might influence the required returns and thus shows up in the yield. Low liquidity might make it difficult to trade at the intrinsic price. The yield thus has to be higher to accommodate the potential loss from trading in a thin market.

General critique of methods and concepts

The methods being employed in this thesis are standard for asset pricing and corporate finance studies, with some extensions. In this section I will describe the critique that others have presented against the CAPM, and lay out my own view on liquidity risk and any potential tax-influence on bond returns.

There are two main pieces of critique of the CAPM, first Roll (1977) showed that due to a mathematical equivalence between the existence of a return beta representation and the market portfolio's mean-variance efficiency[6] a test of CAPM require complete knowledge of the true market portfolio's composition. The CAPM includes the total wealth portfolio returns and this total wealth portfolio cannot be identified, so if the CAPM is "rejected" - it cannot be known if this is because the CAPM is wrong or if the data on the wealth portfolio is wrong. The second critique is that one period mean-variance portfolios do not ensure the maximum expected utility over more than one time period. Hakansson (1971) shows that the set of one period mean-variance efficient portfolios *can* intersect the set of multi-period efficient portfolios. That is, an optimal portfolio of the static CAPM can be something that an investor should want to hold to optimize his life-time consumption, but it is not necessarily so. A simple example where the one-period-CAPM fails over a longer time span is when there is insolvency after the first period, which is possible in some one-period mean-variance optimal portfolios. The default in the first period means no additional utility can be generated from the portfolio, which makes it an obvious inferior portfolio over more time periods. A multi-period solution prices the default risk in a better way than a static CAPM solution. In this example with he defaulting portfolio the mean-variance concept of the static

[6] A portfolio is "mean-variance efficient" if there are no portfolios with lower expected variance for any expected mean return.

CAPM is not necessarily wrong, but it is less useful. Despite these shortcomings of CAPM it is still a much used tool for studying portfolio risk-returns and useful for indicating the effects of diversification.

The liquidity risk is used in many studies[7] as one factor that might explain the yield spread. The liquidity problem arises when a party wants to trade in the market, but cannot do so at the "correct" price, or the trading in itself moves the price due to thin liquidity. In essence there are two arguments for a priced liquidity risk; asymmetric information among investors or systematic shocks in returns from bond-runs.[8] If the owners of corporate bonds are expected to have more information than the market in general, then prospective buyers will require a discount to buy the bonds. The asymmetric information can thus give rise to a liquidity effect in the market, in the sense that liquidity is low and the market price deviates from the intrinsic value. The potential for bond-runs is real and there has just (in 2007) been one run on U.S. sub-prime bonds. The effect of a bond-run is similar in appearance to a default risk, but with more simultaneity in timing.

Despite the large loss in default, the covariance terms for corporate bonds returns against the market returns are typically small, so the "bond-run risk" might not play a major role in bond valuation. Also, it cannot be ruled out that the estimates of liquidity co-vary with something like uncertain credit quality, and is not liquidity driven at all. In any case, there are three main ways to estimate the liquidity factor; the difference between the bid and ask spread, the correlation between volume and price changes, and traded volume. In my second paper I have collected and constructed eight liquidity measures that are based on the correlation between traded volume and returns. The correlations between these liquidity measures are low, leading me to believe that several of them do not measure liquidity in a meaningful way. Regardless of this critique, liquidity is a common standard in studies of corporate bond yield spreads, so I apply controls for liquidity in my studies of expected return.

There is a difference in taxation on US government bonds and corporate bonds. According to Elton et al. (2001) corporate bonds are taxed on the state level, but US government bonds are not. That is, an investor pays coupon tax on the coupon from a corporate bond but not on the coupon from a government bond. The difference in taxation status might be important for the size of the credit spread, and hence has some impact on the return differences between corporate and government bonds. Assuming no arbitrage, the relative price

[7] A few recent studies are Ericsson & Reneby (2003), De Jong & Driessen (2005), and Chen et al. (2005).

[8] When there is a bond-run buyers leave the market place, and liquidity dries up.

between a corporate and a government bond should be such that if there were a risk free corporate bond, it would give the same return after investor taxes as a government bond. In contrast to the effect in yields, the impact from taxation can be expected to be quite small for the study of expected returns.[9]

Aspects on data

There are few sources of corporate bond prices with high quality data. In my search for data I have encountered the Lehman Brothers database (also known as the Warga data base), FISD database, NASD traded bond prices (TRACE), Altman's database on defaulted bonds, and Thomson Datastream. There are advantages and disadvantages with all of these databases. I chose to use the Thomson Datastream[10] for two reasons; I had readily access to it and the results from studies that have used this database are not markedly different than other studies.

The available data series in Datastream on bond returns and company accounting data cover short time periods, since it is difficult to get longer series with sufficient quality. The bond return series in the sample cover 4.5 years (monthly data) and the accounting data cover 15 years (yearly data). The few observations make estimations uncertain both for GARCH[11] and mean reversion estimates. To decrease this problem I have collected large cross sections of bonds and companies respectively. The large cross sections help in the sense that any information in the time periods which is general for more than one bond/company can be extracted. However, in a sense the results are contingent on a relatively short time period, and are thus to some extent time-conditional.

There is an inherent problem with the data collection on corporate bonds. Even if bonds are listed at an exchange it is by no means certain that all trading participants report their transactions. There can be many reasons for this, ranging from a wish to avoid the revelation of proprietary information to practical ones, such as the costs and effort associated with reporting. This

[9]Consider a fixed taxation premium in the price of Δ. The "traded" price is thus $P = P^* + \Delta$ where P^* is the intrinsic price. The difference in measured return between the traded price and the price without the premium at time t is then $R = \frac{P_{t+1}}{P_t} - \frac{P^*_{t+1}}{P^*_t} = \frac{\Delta(P^*_t - P^*_{t+1})}{P^*_t(P^*_t + \Delta)}$. Hence if the premium is small or the price does not change between t and $t+1$ there is no difference at all in the measured return. Note that this reasoning applies to other reasons for premiums in the price as well, such as liquidity.

[10]Limited information can be found on the Datastream web page, www.datastream.com. For more information contact Thomson Financial through www.thomson.com.

[11]GARCH is a model of the error terms in an estimation, where large error terms follow on large and small error on small.

problem is being addressed by the market data collectors and the situation might improve over time. Specifically, since 2002 National Association of Securities Dealers require their members to report all corporate bond trades in the TRACE system.

Essays

Default risk in corporate bond pricing

The purpose of the first paper is to study the impact of default risk for the expected required return of corporate bonds. Default occur when a firm does not service its debt, so it is natural to think about default as a risk that only affects the company that defaults. Market equilibrium models implies that risks that only influence single securities should not get any return compensation if the risks can be diversified away. Having said that, most text-book models for valuing corporate bonds include the probability of default in the calculation of the expected pay-off, but not in the discount factor.

For a single zero coupon bond, the company receives the value (V_t) against the promise of a repayment (X) in the future. Investors realize that the uncertain payment of X in the future is not as good as having X today, so the investors discount the repayment with $(1 + \rho)$. A simple model of this relationship would be;

$$V_t = \frac{E\left[X_{t+1}\right]}{1+\rho}, \tag{4}$$

where $E[\cdot]$ represents the expectation operator. There are two direct sources and one indirect source of uncertainty for the calculation of the value (V_t):

- The payment is contingent upon the company's ability to pay in the future. The non-payment of X_{t+1} is either the default or the more severe bankruptcy event. In both cases the owner of a corporate bond can expect to receive X_{t+1} or less.

- The discount rate (ρ) is not known since it is contingent on the risk of the expected future payment. The discount rate depends on the uncertainty of repayment, the time value of money, investor risk attitudes and wealth endowments.

- An indirect risk in bond pricing models is the liquidity risk. If the owner of a bond wishes to exchange the bond for cash, he has to access the market. If the investor gets paid less than the intrinsic value of the bond ($P < V$), there is a premium.

For a portfolio with a large number of bonds, an individual bond might not be so important for the value of the portfolio. If we assume that $V_T^1 = 0$ for one bond, we still have about the same value in the portfolio, or $V_t^P|(V_T^1 = 0) \approx V_t^P|(V_T^1 = 1)$. However, if there are many bonds that will expire worthless at the same time (systematic risk) then the approximation is no longer valid.

I use a regression analysis framework to analyze this issue. In a first step the systematic risks of corporate bonds are estimated. The estimations are done both using standard OLS and GARCH for the entire sample, and subsamples based on ratings, industries and maturities. The idea with the tests of the different cross sections is that there might be other systematic risks and I do not want to attribute their explanatory power to the default risk.

When companies default on bond payments, the bonds are typically still worth something. In the next step of the analysis the value of the bond in default is estimated with a simple event study method. In the final section the default risk is calculated from the estimates of systematic risk, control variables (liquidity and yield curve changes), and a variation of market prices of risks and recovery rates. The idea is to see what estimates of default risk the market sets in the calculations of the expected returns.

In the empirical study of the first paper, I find that corporate bonds have a small systematic component in their returns. The market beta correlates with credit quality. If the sample is divided into industry or maturity portfolios, the systematic component is weak. The results imply that there is systematic variation that has to do with the credit risk. Perhaps a bit surprising, the size of the systematic factor is not linear in credit quality (as measured by ratings) but seems to depend on whether the bond has an investment grade status or not.

The remaining idiosyncratic default risk is extracted after adjusting for the systematic component of the default risk. There are two notable results; first, part of the idiosyncratic default risk is priced and, second, the estimates of the remaining default risk exceed the actual historic default rates. These two results imply that the bond market appears to exaggerate the default risk associated with investments in corporate bonds. The exaggeration of the default risk is consistent with the yield spread puzzle. However, the consistency with the yield spread puzzle is *after* a correction for the systematic default risk.

The results are consistent with the findings in earlier studies on yield spreads, expected returns of corporate bonds, and recovery rates. The size of the estimated corporate bond beta (0.06) is in the same neighborhood as Weinstein (1981) and the difference between ratings categories (Investment grade between -0.01 and -0.13 and non investment grade between 0.11 and 1.48) in Cornell & Green (1991) is also found. The diverse findings on corporate bond returns can be explained by the existence of both systematic and idiosyncratic default risks. The results confirm the excess returns for corporate bonds found by Driessen (2005). The estimated recovery rates are similar to the ones estimated by Moody's, but there seems to be a price drift after the default event that is investigated in the second essay of this dissertation.

The estimates of the market risk with GARCH errors suggest that the variance specification removes part of the effect from rare events, in this case the default. It could be tested as a general method of removing rare events and thereby give a better going-concern estimation of the market beta. The controls can be improved, with for instance better measures of liquidity risk. The data from the study covers a relatively short time period. A different and longer time period could confirm or reject the estimates, increasing the usefulness of the results. The theories are general and the return data is from US Corporate bonds, it could be useful for valuation of non-US bonds to know if the same parameters are valid for them.

Returns to defaulted corporate bonds

The recovery rate in a default situation can be important for the value of a bond also before default. The recovery rate matters for the estimation of the expected payment ($E[X]$). Hence there is a demand for statistics on the recovery rate and these are presented yearly as a matter of routine by rating agencies. However, the methods for calculating the recovery in default take a myopic view of the value of the bond. The standard estimations narrow down the time period studied to one month and disregard what happens to bond prices afterwards. From the first essay there is an indication that there might be high returns after default. However, as the estimates in the first study are not risk adjusted, any conclusions on returns are premature. I focus on calculating the risk adjustment of returns after default in this study.

A company defaulting on its obligations is typically a powerful signal to the rest of the world that there is something amiss with the business. Some companies manage to turn around and become successful but others go into bankruptcy. If a company declares bankruptcy, there is a process where the creditors can take over the assets of the company. Hence debt can be transformed into equity. This means that corporate bonds have a non-zero probability of becoming equity, where defaulted bonds have a much higher probability than non-defaulted bonds. Essentially these bonds are something in between debt and equity in terms of future payments.

The sample used in this study consists of corporate bonds that default, meaning that before default it is a choice based sample and after default a random sample of defaulted bonds. The bonds do not default at the same time, making adjustments to the sample necessary. The bond returns are then regressed against risk factors to determine the co-variation with the risk factors. The risk factors considered are a market factor, eight liquidity factors, and the Fama & French (1992) factors. Empirically I find that it is primarily the market factor that is important after default.

The prices of defaulted bonds vary, and if they are held up to nine months after default the 'recovery rate' differs. The recovery rates are discounted with risk adjusted interest rates to make them comparable to the recovery rate at default. Finally the differences between the 'at default' recovery rate and the future recovery rates are tested.

A defaulted bond is something in between debt and equity which means that it will have characteristics that are a mix of bond and equity. I find that before the default event corporate bond returns co-vary with liquidity, the market factor and the Fama & French (1992) factors. This means that the corporate bond returns to some extent behave like bonds (due to the liquidity factor) but to a large extent also like shares (due to the market factor). The choice based sample of corporate bonds has higher market beta (0.25-.30) than a beta for a random sample of corporate bonds (0.06), indicating that there is a higher default risk. After the default the corporate bond returns do not co-vary with the liquidity factor and to a larger degree with the market and Fama and French factors. That is, after default the bonds behave nothing like bonds and somewhat like shares. The market beta is still significant and higher (0.46-0.53) than before default. The increasing market beta during the process shows that there is a transition process towards equity.

From the first paper, it seemed that returns to defaulted bonds were high. There are, to my knowledge, no previous studies on defaulted bond returns (or recovery rates) in time-series. The value of a defaulted bond is very uncertain in the sense that there is limited information on what the repayment will be. In terms of equation (4), $E[X]$ is uncertain even if the cross section of recovery rates has been measured with some accuracy. At the same time a defaulted bond is a financial asset and should hence be priced so that the expected return is sufficient to compensate for the risks associated with it.

In the empirical evaluation of defaulted bonds, there are significant excess returns, after controlling for market risk. I divide the sample into seniority, industry and return portfolios. The expected return is positive for almost all portfolios, indicating that the result is quite robust. Having said that the explanatory power for many of the tests is quite low measured as R^2. Only a small portion of the expected return can be explained by the risks tested for. The positive excess returns after default can be interpreted as a mispricing at default. To test this idea of mispricing the bond prices nine months after default are discounted to the default date using a risk adjusted interest rate. This test is weaker than the returns tests, since there are much fewer observations. The present value of the recovery rate nine months after default differs by ten percent from the recovery rate at default, but the difference is not significant.

The study answers the question if the returns on defaulted bonds are higher than expected. This is interesting since it means that there is a wealth transfer from the seller to the buyers after a default situation. The risk aversion of investors might explain part of the apparent mispricing. Now, the question is if this is a more general phenomenon and if it applies to other highly distressed assets as well, such as mortgage bonds. It is possible that the period 2001-2006 is special in some sense. As for the previous essay an increase in the scope (geographical, time and instruments) would increase the usefulness of the estimates, making the model useful for valuation purposes outside the set of US corporate bonds.

Capital structure choices

This paper deals with a different aspect of financial risk. The problem studied here is how companies choose or obtain their capital structures. The capital structure is how companies have financed their assets, i.e. the mix of owners equity and debt. There are many ideas on how companies choose their capital structures. A main idea being tested is that the financing of assets are mainly driven by the company's historical profitability. This idea of historical chance is a part of the pecking order theory. The theories on capital structure choice (or leverage) are not always mutually exclusive in their empirical predictions. A simple example of this is that if a firm increases its leverage it can support both the trade-off and the pecking order under some circumstances. I.e. if the firm has had too low leverage it moves to a trade-off point and at the same time chooses debt over equity as the pecking order predicts it should. This problem is handled by testing the theories separately. I start with testing the trade-off theory, the pecking order theory, and then finally test the idea of historical chance against the trade-off theory.

There are several problems associated with the tests of the trade-off theory. First, in line with other research the trade-off theory is tested as a mean reversion process[12], where the mean is dependent on a number of factors related to tax shields, non-debt tax shields, future profitability, etc. However, it is not evident that a trade-off is best tested as a mean reversion process in the data. For instance if the movement to an optimal trade-off is instant, then the measure of convergence speed will be zero and I would reject the trade-off even though it might be true. As it turns out this is not a problem in the empirical tests, since the parameters that are supposed to influence the optimal trade-off give a relatively fixed assessment of the optimal leverage and the companies change their leverage slowly. I.e. the problem is not so large since the predicted leverage does not deviate from the mean very much.

The trade-off theory is tested using a common mean reversion framework. There are few rejections of the trade-off theory, both for the pooled sample and for the industry portfolios. To decrease the likelihood of accepting the trade-off theory when it indeed is false, a second stricter test is designed. The significance levels then decrease, but the pooled sample and the industries where I have a fair number of observations still have significant mean reversion parameters. This leads to the conclusion that the trade-off theory, as modeled in a mean reversion test, cannot be rejected as a description of how company leverage develops over time. However, there is a puzzling result in the estimation of the optimal leverage, where the earnings coefficient has a negative sign when regressed against leverage. Higher earnings were expected to facilitate more borrowing and thereby increase the leverage. More borrowing increases the size of the tax shield, which is valuable to the company.

The first tests of the pecking order theory give no support to this theory. The pecking order hypotheses tested can in no instance replace the alternative hypotheses. It does not help if the pecking order hypotheses are combined with sticky dividends (meaning they change little from year to year), they can still not replace the alternative. Also in a joint test of marginal financing for all companies in the sample, the pecking order is rejected. The trend of decreasing leverage in the sample does however make it difficult not to reject the pecking order, since the tests are constructed around marginal financing. In total the support for the marginal debt financing of the pecking order theory is weak, it seems like companies do no use debt for their marginal financing needs. However, there are clear indications that leverage and profitability are negatively related, in line with the prediction from the historical chance.

[12]Mean reversion is when a series tend to move towards its mean. For example when leverage is high it can be expected to decrease until it reaches its historical mean and vice versa when leverage is low.

The last test is a joint test of historical chance and the trade-off theory. This is done by testing a model that incorporates a mean reversion and a drift parameter. The mean reversion is the test of the trade-off and the drift term should capture the historical chance idea. Both the mean reversion parameter and the trend parameter are statistically significant. The support for the trade-off theory is strong in the Swedish sample and the profitability based historical chance is the stronger part of the pecking order.

The test results for the trade-off theory are likely due in part to the low power of the normal trade-off tests, as described by Shyam-Sunder & Myers (1999). To increase the power of the testing, a new test is introduced. Still the result support the trade-off theory, like for Hovakimian et al. (2001), and Fama & French (2002). The pecking order theory is only supported in the historical chance aspect.

There is an interesting alternative interpretation of the results. Given that the optimal leverage changed "dramatically" in the early nineties' there is a long adaptation process that gives a long run trade-off theory that is driven by the availability of internal funds. A new unanswered question is then why companies have not accessed the capital markets to remove the long run imbalance in leverage. There is also a problem with the current state of the empirical tests that needs to be addressed in future research. The theory linkages to empirical tests seem weak and open for alternative interpretations. Perhaps it might be more useful to study why companies issue debt or equity rather than the leverage, like for example Helwege & Liang (1996) do for IPO companies.

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Part II

Papers

Chapter 1

Default Risk in Corporate Bond Pricing

Abstract

This paper provides a model for how the corporate bond default risk influences the systematic risk and an empirical analysis of the systematic and idiosyncratic parts of U.S. corporate bond returns during 2001-2005. The average corporate bond beta is low and positive (0.06). Investment grade bonds have negative betas (between -0.01 and -0.13) and non-investment grade bonds have positive betas (between 0.11 and 1.48), but both groups have similar within groups systematic risks. When controls for interest rate and liquidity risks are introduced there are still remaining default probabilities, implying that the default risk is in part systematic and in part idiosyncratic.

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1.1 Introduction

Default risk is presumably a part of every valuation of securities with credit risk. The default risk can be both company specific or systematic. If a company has an increased risk of default independent of how other companies fare, then that risk is idiosyncratic. If companies tend to have increased default risks at the same time, then the default risks is systematic. The split between systematic and idiosyncratic risk in corporate bond returns is the central question in this paper.

There is evidence that there are systematic factors in the pricing of credits. Weinstein (1981) studies the systematic risk of U.S. corporate bonds from 1962 to 1974 and finds systematic risk in bond returns. Chen et al. (1986) finds that the bond risk factor contributes significantly in explaining excess stock returns. Cornell & Green (1991) finds that low grade bonds and high grade bonds have different exposure to market risk. Fama & French (1993) find that two factors (a term structure and default premium) explain the average return on corporate bonds. On the other hand Elton et al. (2001) find that the lion's share of the bond returns in their sample is non-diversifiable and argues that this is why there is a risk premium. Driessen (2005) decomposes corporate bond spreads, motivating his study by earlier findings that corporate bonds earn excess returns also after accounting for the likelihood of default. Berndt et al. (2006) find a common time-series variation in firm specific default risk. Most studies support the notion that there is a systematic component in credit prices.

In this study, the existence of systematic risk is confirmed using standard statistical methods and GARCH-estimation.[1] GARCH is used for two reasons, the data-set has more observations in later than in earlier time periods and the variance on corporate bond returns can not be expected to be constant.[2]

There have been a few suggestions as to why there is systematic risk in

[1]GARCH is short for Generalized Autoregressive Conditional Heteroscedasticity. The simple process used here is a GARCH(1,1), where (1,1) indicates how many lagged error terms and variance terms there are in the model, $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$, where h_t is the estimated variance (or more precisely $E\left[\varepsilon_t^2 | I_{t-1}\right]$, the expected squared residual given the information I_{t-1} available), ε_{t-1}^2 the lagged error term squared, h_{t-1} the lagged variance estimation. To estimate the conditional variance, a starting point is needed; here the unconditional variance has been used. The GARCH class of model was introduced in Bollerslev (1986).

[2]The mean portfolio returns can be expected to have a larger variance when there are few returns in earlier periods and smaller variance in later periods when the number of observations increase. A safe bond has a lower variability of returns than a risky bond. A corporate bond can migrate between these different states, and do in some of the sub-sets of data in this study, so GARCH estimation improves the estimates of the coefficients.

credit pricing, but three factors have mainly been used to explain the expected return on the credit market since at least Fisher (1959). Fisher uses bankruptcy and liquidity risk (marketability) as key factors in a model that determines the value of a corporate bond. Merton (1974) uses three factors, the risk free interest rate, the specific provisions of the bonds, and the bankruptcy risk. Elton et al. (2001) use the risk free rate, the expected bankruptcy probability, a tax premium, and a risk premium for estimating bond spreads.[3] Collin-Dufresene et al. (2001) find that credit spread changes are driven by a common factor. Martell (2003) find two factors driving the size of the credit spread. Longstaff & Schwartz (1995) added the risk free interest rate and assets return factors in their model. The main empirical result is that the asset values of a firm are correlated with changes in the level of interest rate and this influences the value of risky fixed income securities. Collin-Dufresene et al. (2001) and Martell (2003) find that one or two unknown factors determine the size of the bond spreads using principal component analysis. Ericsson & Reneby (2003) find their corporate bond pricing errors to be largely diversifiable, but also that there is a small but non-negotiable systematic risk.

It is confirmed in this study that the returns of corporate bonds are influenced by systematic factors during the period of 2001 to 2005. Corporate bonds are not a homogeneous group of instruments; they contain both relatively safe instruments and high risk "junk" bonds. In this study two main drivers of systematic risk are found; the investment grade bonds are primarily influenced by the interest rate risk and the non-investment grade bonds are primarily influenced by a systematic default risk. The strongest evidence for these two factors can be seen if the sample is divided into portfolios using Standard & Poor's (S&P) ratings. The matter is not so clear if the portfolios are constructed using industry or remaining time to maturity, suggesting that default risk is a more important factor for the systematic risk than operating risk and interest rate risk.

Apart from the three most common factors, there are other suggestions. Cambell & Taksler (2003) for instance suggest that equity volatility helps explain the corporate bond yield spread in the cross-section. In their study equity volatility explains as much of the corporate yield spreads as does the rating. The equity volatility can be expected to correlate with other factors, such as the default risk.

Different sources and types of data on credit returns have been used to study systematic factors in credit pricing; bond fund returns (Cornell & Green

[3] A bond spread is the difference in yield between two bonds with the same maturity. Elton et al. (2001) use the difference between corporate bonds and government bonds.

(1991)), Credit-Default-Swaps (Berndt et al. (2006), Berndt et al. (2004), and Saita (2006)), and corporate bond returns (Weinstein (1981), and Driessen (2005)). In this study corporate bond returns are used and validates earlier studies and extends previous results. The corporate bond return data is from the same time period as Berndt et al. (2006) who used Credit-Default-Swaps (CDS), making the results comparable. The data includes more than one class of non-investment grade bonds. Elton et al. (2001) focus on investment grade (down to BBB in S&P rating terminology) bonds and might hence miss some cross-sectional variability. In the study of systematic default risk, the lower grade bond returns are potentially important.

Having estimated the systematic risk for bond returns, the loss in default is briefly studied. The loss in default is needed to make the estimations on the remaining default probability. Altman & Kishore (1996) studies the loss in default, and it has been made a matter of routine by the rating agencies (see for instance Moody's (2007)). After systematic risk has been controlled for, there is still default risk present in the sample. In principle the error terms from the systematic risk estimation are then a measure of the size of the remaining default risk. These error terms are used to calculate the "idiosyncratic default risk", the part of default risk not being accounted for by the systematic risks. The idiosyncratic default risk turns out to be substantial (for a 'BBB' bond with market price of risk $\lambda = 3$ percent and a recovery rate of 50 percent the estimated monthly default probability is 0.46 percent).

In the tests of this paper, the default risk is not only systematic, but also idiosyncratic. The investment grade bonds have less systematic risk than the non-investment grade bonds. Even after elimination of the systematic risk and controls for interest rate and liquidity risk, there is a fair amount of default risk left, as measured by remaining default probabilities. Finally estimated idiosyncratic default risks are larger than suggested by the actual default rates as presented by Moody's (2007) and Standard and Poor's, suggesting that investors have a systematic bias in their default risk expectations or that there is some unidentified risk. The higher estimated default probabilities are consistent with the existence of the yield spread puzzle.[4]

The layout of this paper is as follows. In section 1.2 a CAPM based model for estimating the default risk is developed. In section 1.3 the hypotheses are discussed. This is followed by a description of the data in section 1.4. In section 1.5 the data treatment is described. The results are discussed in section

[4]The yield spread puzzle is the notion that the actual historic default rates are not sufficiently high to motivate the yield spreads observed between corporate and government bonds.

1.6. Section 1.6 is divided into three sub-sections. In the first sub-section the systematic risk in bond returns is estimated. In the second sub-section, the loss in default is examined. In the final sub-section the default probabilities are extracted from the return data. The main conclusions of the study are presented and discussed in section 1.7.

1.2 Model

Given that no arbitrage opportunities exist, equilibrium in the asset market can be characterized by the Euler equation of the Intertemporal CAPM (ICAPM). The ICAPM is used since it is convenient to derive equation (1.6) below in these terms. The Euler equation describes the link between asset returns and consumption over time;

$$E_t\left[m_{t+1}\mathbf{R}_{t+1}\right] = \mathbf{1}, \tag{1.1}$$

where m_{t+1} is the stochastic discount factor (SDF), $\mathbf{R}$ is the $(N \times t)$ matrix of N assets gross returns, and $t+1$ is a time period subscript. The equation is independent of which valuation model is used, since it simply states that in expectation the discounted gross returns should be one. The expected gross return can be written as a convex combination of the promised return and the return in the default state for any bond with uncertain repayment, where the "promised" return is the return promised by the issuer of the bond. Hence:

$$E\left[R_{j,t+1}\right] = \pi_{j,t+1}\gamma_{j,t+1}R^{p}_{j,t+1} + \left(1-\pi_{j,t+1}\right)R^{p}_{j,t+1} \tag{1.2}$$

$\pi_{j,t+1} \in [0,1]$ is the probability of default for bond j at time $t+1$, $\gamma_{j,t+1}$ the fraction of the gross return that the investor gets in default, and $R^{p}_{j,t+1} \in \mathbf{R}_{t+1}$ is the return the investor would have received given no default, also known as the promised return. Since $R_{j,t+1}$ is a linear function of $R^{p}_{j,t+1}$, also $R_{j,t+1} \in \mathbf{R}_{t+1}$. In equation (1.2) the recovery rates, and probabilities are set to be exogenous.

The default probability $(\pi_{j,t+1})$ and the fraction recovered $(\gamma_{j,t+1})$ can vary over time and companies. According to Moody's (2002) the average recovery rate for 1982 to 2001 was 41 percent of par value with a median recovery rate of 35 percent. Even if Moody's argues that the recovery rate seems to co-vary with the business cycle it could be a good approximation to fix the recovery rate for shorter time horizons. The true recovery rate is unobservable, but a common proxy is the trading price one month after default, as used by for instance Moody's. Altman & Kishore (1996) find the recovery fraction to be different for different industries, where public utilities, chemical and petroleum have the highest fraction. Not surprisingly, senior debt also tends to have a high recovery fraction. The promised return is the contractual payments of the bond divided with the price of the bond. The price of the bond changes with the interest rate, so the promised return will also change with the interest level.

Since equation (1.1) is valid regardless of asset or portfolio of assets considered, it is also valid for an instrument with the return pattern described in equation (1.2). Using the definition of covariance, rearranging, dropping the bond subscript and introducing $\beta \equiv \frac{cov(m_{t+1},R_{t+1})}{var(m_{t+1})}$ and $\lambda \equiv -\frac{var(m_{t+1})}{E[m_{t+1}]}$, equation (1.1) becomes the beta pricing model[5]:

$$E\left[R_{t+1}\right] = R^{f}_{t+1} + \beta\lambda, \tag{1.3}$$

and since $R_{t+1} \in \mathbf{R}_{t+1}$ equation (1.2) must also satisfy equation (1.3):

$$E\left[\left(\pi_{t+1}\gamma_{t+1} + (1-\pi_{t+1})\right)\right] R^{p}_{t+1} = R^{f}_{t+1} + \beta\lambda, \tag{1.4}$$

where β is the standardized covariance between the bond return and the wealth portfolio, and λ is the market price of risk.[6] The promised return can be taken out of the expectations operator, since it can be observed at time t. The total risk premium depends on the beta, and if gamma is assumed to be constant it can be noted that beta is defined by:

$$\beta \equiv \frac{cov\left(m_{t+1}, R_{t+1}\right)}{var\left(m_{t+1}\right)} \tag{1.5}$$

indicating that the co-variation between an individual return and the SDF determines the size of the beta. Specifically, the beta incorporates information on the default risk, and to illustrate the relationship between the default risk and the beta further; assuming that the recovery rate and the default risk are exogenous then since the promised return (R^{p}_{t+1}) is known at t, expression

[5] The details can be found in advanced text books. Note that the beta pricing model can be rewritten in return-beta form: $E[R_{t+1}] = R^{f}_{t+1} + \beta(E[R^{m}_{t+1}] - R^{f}_{t+1})$, since $E[R^{m}_{t+1}] = R^{f}_{t+1} + \lambda$, where R^{m}_{t+1} is the return on the wealth portfolio.

[6] If it is assumed that $\gamma = 0$, no recovery in bankruptcy, then expression (1.4) conforms with Skogsvik (2006) equation (C2") stated as net returns, $r^{p}_{t+1} = \frac{(r^{f}_{t+1}+\beta\lambda)+\pi_{t+1}}{1-\pi_{t+1}}$, where $r^{p}_{t+1} = R^{p}_{t+1} - 1$ and $r^{f}_{t+1} = R^{f}_{t+1} - 1$.

(1.5) can be written as;

$$\begin{aligned}
\beta \equiv \frac{cov\left(m,R\right)}{var\left(m\right)} &= \frac{E\left[mR\right]-E\left[m\right]E\left[R\right]}{var\left(m\right)} = \\
&= \frac{1-E\left[m\right]E\left[R\right]}{var\left(m\right)} = \\
&= \frac{1-E\left[m\right]E\left[\left(\pi\gamma+\left(1-\pi\right)\right)R^{p}\right]}{var\left(m\right)} = \\
&= \frac{1-E\left[m\right]E\left[\left(\pi\left(\gamma-1\right)+1\right)\right]R^{p}}{var\left(m\right)} = \\
&= \frac{1}{var\left(m\right)}+\frac{R^{p}\left(1-\gamma\right)E\left[m\right]}{var\left(m\right)}\pi-\frac{E\left[m\right]R^{p}}{var\left(m\right)}
\end{aligned} \tag{1.6}$$

In equation (1.6) the beta is a function of the default risk, the promised return, SDF, and the recovery rate. This CAPM based model gives some guidance on how the expected default risk influences the systematic risk, as measured by the beta. Since the promised return and expected SDF are positive, the recovery rate (γ) is between zero and one, an increase in the default risk increases the beta. Furthermore, if the recovery rate (γ) is high, the default risk can be expected to have little influence on the beta. Safe industries, such as utilities, should thus have less influence from default risk in their beta.

If the returns are assumed to be log normally distributed, the investment opportunity set is constant, then equation (1.3) coincides with the Merton (1973) continuous time analog of the capital market line. If the investment opportunity set is not constant, the equality only hold under the assumptions of Bernoulli logarithmic utility, or non stochastic interest rates, or that all assets returns are uncorrelated with the interest rate.

As a side note, equation (1.4) can be used to value corporate bonds. If x_{t+1} is the promised payment at time $t+1$ and $R_{t+1}^{p}=\frac{x_{t+1}}{p_t}$ holds, the value of a zero coupon can be estimated as;

$$p_t = \frac{\left(1-E\left[\pi_{t+1}\left(1-\gamma\right)\right]\right)x_{t+1}}{R_{t,t+1}^{f}+\beta_{t,t+1}\lambda_{t,t+1}} \tag{1.7}$$

and summing T zero coupon bonds to a T period coupon bond;

$$p_t = \sum_{i=1}^{T}\frac{\left(1-E\left[\pi_{t+i}\left(1-\gamma\right)\right]\right)x_{t+i}}{R_{t,t+i}^{f}+\beta_{t,t+i}\lambda_{t,t+i}}\prod_{j=1}^{i-1}\left(E\left[1-\pi_{t+j}\right]\right). \tag{1.8}$$

Three risks associated with holding corporate bonds can be seen in equations (1.7) and (1.8). Three of these risks are the default risk (π), adverse changes in the recovery rate (γ), and interest rate risks (R^f, β, and λ). The liquidity risk is the fourth risk in this study, and it is the expected deviation from p_t when the investors wish to sell their corporate bonds.

1.3 Hypotheses

If the default risk plays a role in the pricing of corporate bonds, it should be discernible in the returns. Discounts in price translate over time to returns. If the discount is too large, then the corporate bond will exhibit too high returns and vice versa. From equations (1.7) and (1.8) there are a few suggestions on which risks are important. Whether investors holding corporate bonds are compensated for these risks is an empirical question. Fama & French (1993) found no difference between the expected returns for corporate bonds and the risk free rate. Their finding coupled with the four risks are the basis for formulating the claim;

Claim 1.1 *The expected return of a corporate bond equals the risk free rate of return.*

If this claim is valid, then a CAPM based model applied to the corporate bond returns should not exhibit abnormal returns and it should not be possible to measure the systematic risk with any precision. In other words, the difference between the expected corporate bond return and the risk free return should be zero, making parameter estimates from an econometric specification of equation (1.10)(p.39) below insignificant. Even if there is a difference in the returns, it is possible that the average of the cross-section does not reflect this, i.e. it is possible that $E\left[R^{bond}\right] = R^f$. To rule out this possibility the return data will be tested on three sets of portfolios based on rating, industry and maturity. The ideas are that the default risk should be visible in the ratings portfolios, the variability in recovery rate in the industry portfolios, and the interest rate risk in the maturity portfolios.

The gravity of a default event is important for the possible default return, i.e. it matters how much is lost. Given that the investors have efficient expectations, in the sense that they on average manage to correctly estimate the loss in a default situation, the expected loss can be estimated from the sample. From the model in equation (1.4)(p.30) it is clear that an estimate of the loss in a default situation is necessary to calculate the default probability. In earlier studies the loss in a default situation is estimated as a point estimate.

To simplify slightly, for example Moody's (2007) estimates the recovery rate by measuring the ratio of bid price (30 days after default) to face value. This procedure might be sufficient, but there might also be a process where investors gradually realize that the prospects of the company are getting worse. This might indicate a longer period preceding the default of poor returns. The returns after the default are also important and little is known of what happens with returns after the default. In the beta equation (1.6)(p.31) and the pricing equations above, the recovery rate is part of determining the beta and the price of corporate bonds. To estimate if the recovery rate estimation is biased, the following claim will be briefly examined;

Claim 1.2 *The loss from a corporate bond default is not a one time loss.*
To study the default process an event study method will be employed. All the bonds that are in default ex-post will be used to study the process. The returns pre- and post the default time periods will be assigned dummy variables and tested against the null hypothesis of no difference in returns.

If there is systematic risk in the returns of corporate bonds, can the default probability explain it? The interpretation would be that the probability of default, as measured in the corporate bond returns, is the propensity for simultaneous default, or a systematic default probability. To test this setting, the following claim is examined;

Claim 1.3 *The return from a corporate bond is explained by the default risk.*
The systematic risk components, as estimated in the examination of the first claim, will be used to test for a systematic default probability, with elimination of a few confounding factors, such as ratings, industry, and changes in the yield curve. Now even if there is a systematic default risk this might not be the entire "default risk story". To see if there is also idiosyncratic risk in corporate bond pricing the idiosyncratic default risks are extracted from return data to estimate, with controls for interest rate and liquidity risks.

1.4 Data

The data set was collected from Thomson/Datastream and originally contained some 7,011 U.S. corporate bond price series. The US corporate bond market has the largest depth and is the largest in relation to GDP[7], making

[7] Rajan & Zingales (1995) show that in 1986 the US corporate bond market amounted to 23.27 percent of GDP. The second largest in relation to GDP that Rajan and Zingales

it an obvious candidate for the study of corporate bond returns. In the sample there were bonds with negative accrued coupons and monthly returns less than -100 percent and these return series were eliminated (1 percent of the sample). Furthermore, the sample was cut to eliminate bonds with non-fixed payments (floating rate, variable rate, and graduate rate bonds), leaving 6,877 fixed income and zero coupon bonds. Out of the remaining bonds, 832 (12.1 percent) are convertible into shares and these bonds were also cut out, leaving a grand total of 6,045 bond price series in the sample. The sample contains U.S. industrial bonds that had not matured at the end of June 2005, and include both defaulted and dead bonds. Out of the remaining bonds, 204 (3.37 percent) bonds had had a default event and 58 (0.96 percent) bonds were dead. The inclusion of defaulted and dead bonds[8] should alleviate survivorship bias.

Table 1.1. Sample distribution.

Status	Payment	Fixed Income	Zero-Coupon
Active	Defaulted	199	2
	Not defaulted	5,772	14
Dead	Defaulted	3	0
	Not defaulted	55	0

The sample of U.S. industrial bond consists of fixed income and zero coupon bonds. The sample includes defaulted and dead bonds that are no longer being traded on the last of June 2005.

The data include prices from December 2000 until June 2005. The prices are the last traded prices at each month end, giving a maximum of 54 return observations for each bond, or about 4.5 years. The average number of return observations per bond is 33.4 and in total there are 201,768 observations. The sample is by construction sparser in the earlier periods and more voluminous in the later periods. In later periods there are more bonds with shorter time to maturity. The comparatively short period is not only a shortcoming since the bankruptcy probability can be expected to vary less during a shorter time period. Unfortunately the business cycle can be expected to have an influence on the bankruptcy probability and the short time horizon makes it difficult to adjust for the business cycle.

The price data is transformed into log returns.[9] The log returns are calculated as;

$$r_{j,t} = \ln\left(\frac{P_{j,t} + A_{j,t} + C_{j,t-1,t}}{P_{j,t-1} + A_{j,t-1}}\right), \tag{1.9}$$

presents is Canada at 7.42 percent.

[8]Dead bonds are not traded anymore at the end of June 2005. Defaulted bonds are in default, but might still be traded.

[9]The returns are assumed to have a log normal distribution.

where $P_{j,t}$ is the clean price (excluding the coupon) of bond j at time t, $A_{j,t}$ is the interest accrued on bond j at time t, and $C_{j,t-1,t}$ is the coupon payment if there was one in the period between $t-1$ and t. Throughout the paper lower case r denotes log returns and upper case $R = (1 + r)$ denotes gross returns. The payment in a bond transaction is the clean price plus the accrued coupon (also known as 'dirty price'). The risk free return was calculated using 30-day U.S. treasury bills, where the 30 day rate was a linear combination of the two bills closest in maturity. Unfortunately a large number of bonds could no be matched with an ICB code.

Table 1.2. Sample portfolio return statistics (yearly basis).

Asset	Number of Assets	Mean	Std. Dev.	Skewness	Excess Kurtosis	Auto-corr.	Jarque-Bera	
Entire sample	6,045	-2.28%	5.63%	-0.52	-0.39	-0.09	2.76	
Risk free return	1	2.12%	0.43%	1.69	2.37	0.83	38.34	***
S&P 500	1	-2.19%	15.66%	-0.44	0.06	0.08	1.77	
Wilshire 5000	1	-0.35%	15.90%	-0.49	-0.14	0.12	2.20	
AAA	60	0.74%	6.35%	-0.76	1.59	-0.30	10.81	***
AA	104	4.42%	6.54%	0.12	2.86	-0.12	18.57	***
A	947	9.78%	9.02%	2.92	17.38	0.04	756.25	***
BBB	1,617	3.38%	6.10%	-0.47	1.65	0.01	8.11	**
BB	665	-6.38%	7.82%	-0.65	1.57	0.08	9.41	***
B	1,094	-19.12%	18.04%	-2.74	13.97	0.00	507.02	***
CCC	348	-23.14%	31.78%	-4.94	29.99	0.14	2243.11	***
CC	14	-6.70%	20.72%	-0.91	2.24	-0.10	18.46	***
C	7	-76.45%	53.37%	-1.58	3.56	0.21	49.20	***
D	10	-45.69%	65.75%	-6.32	43.24	-0.04	4565.12	***
Not Rated	495	-42.37%	52.83%	-4.78	24.70	-0.06	1578.38	***
Not Available	684	-2.17%	9.40%	-0.82	5.19	0.00	66.61	***
Oil&Gas	185	2.71%	7.00%	0.31	2.60	0.06	16.02	***
Basic Materials	235	3.43%	5.01%	-0.61	1.19	-0.01	6.49	**
Industrials	529	2.28%	5.49%	-0.52	0.36	-0.18	2.76	
Consumer Goods	475	2.63%	6.63%	0.61	3.88	0.01	37.15	***
Health Care	189	-2.82%	13.67%	-5.60	37.08	-0.05	3376.51	***
Consumer Services	502	-2.80%	8.44%	-2.44	10.84	-0.21	317.77	***
Telecomm.	76	2.25%	10.16%	-1.23	6.38	0.15	105.16	***
Utilities	330	0.18%	7.56%	-0.61	0.51	0.09	3.81	
Financials	53	-13.10%	13.32%	-2.06	5.52	0.06	106.78	***
Technology	167	-8.83%	13.19%	-4.07	22.46	-0.11	1284.04	***
No ICB	3,304	-4.71%	6.12%	-0.80	0.03	0.01	5.75	*
-1 Year	177	-2.49%	4.17%	-1.46	4.88	-0.04	72.83	***
1-2 Years	373	-3.86%	3.33%	-0.17	-0.26	-0.02	0.40	
2-5 Years	1,507	-8.35%	8.61%	-3.39	16.89	-0.09	745.60	***
5-10 Years	2,483	-0.67%	5.83%	-0.17	-0.33	0.07	0.51	
10-15 Years	416	1.92%	7.60%	-0.44	0.29	-0.13	1.96	
15-20 Years	257	22.70%	7.45%	-0.16	0.15	-0.02	0.30	
- 20 Years	832	3.64%	7.62%	-0.97	2.35	-0.02	20.83	***

The skewness and excess kurtosis measures $(E[\frac{X-\mu^4}{\sigma^4}]-3)$ have been adjusted for sample bias. For the Jarque & Bera (1980) test of normality ***, **, and * indicates a normal can be rejected at the 1, 5, and 10 percent level.

The Jarque-Bera test statistic rejects normality at the one percent level of confidence for most portfolios in the sample, based on sector, S&P rating.[10] For two sectors and a few maturity portfolios normality cannot be rejected. The negative skewness of the entire sample is in line with results on the S&P 500 and Wilshire 5000 stock indices. The negative excess kurtosis is larger than the excess kurtosis of the stock index returns during the sample period. The sample period seems to be atypical for stocks since a higher excess kurtosis could have been expected.[11] Since all the reported portfolios, based on S&P rating and sector, have positive excess kurtosis, it seems somewhat strange that the entire sample exhibits negative excess kurtosis. The reason for this is that the portfolio formation process gives rise to a cross-sectional smoothing, i.e. a single extreme return has less impact in a larger portfolio than in a small. The sample has been checked for serial dependence and the first order serial correlations are reported. The standard errors for the first order serial correlation coefficients are not sufficient to reject the null hypothesis of no serial correlation, except weakly for the 'Industrials' and 'Consumer services' portfolios.[12] Serial correlation of higher order has been examined, but there were no significant estimates. The non-normality of the returns distributions mean that confidence intervals should be interpreted with some care.

Until the 1990's it was common to embed call provisions in corporate bonds. The call provisions allows the issuers to redeem bonds before their nominal maturity dates. Duffee (1998) finds that the use of callable bonds decreased in his sample of U.S. industrial firms from 1985 until 1995. 5,373 bonds out of 5,755 were callable in his sample in January 1985 and a decade later, in 1995, about half the sample consisted of non-callable bonds (2,814 out of 5,291). Out of the 6,045 bonds in this sample 2,109 are callable (35 percent). The call provisions are not necessarily a problem, since the call-date can be viewed as a maturity date, and this would bias the sample towards a shorter horizon. The call provisions have option values and this can influence the returns of the bond. The returns from the options depend on changes in volatility and the type of imbedded option. The call-date is within two months after the last date of the sample for about 589 bonds (9.7 percent). The issuers

[10] The results are the same when portfolios are formed on Moody's rating, default or non-default, convertible or non-convertible, but these tests are not reported.

[11] Excess kurtosis is often mentioned as a typical characteristic of U.S. stock returns, both for individual firms and indices, see for instance p. 17 in Campbell et al. (1997). The authors also report in Table 1.1 a figure for excess kurtosis of 4.14 for monthly return on an equal-Weighted index from the period 1962-1994.

[12] These figures are not reported, but the standard errors were estimated using a GMM procedure with the first four moments of the normal distribution and one moment with one lag.

tend to exercise call provisions only in an environment where interest rates are declining, since then the issuers can refinance at lower interest rates. During the sample period, the bonds with and without a call-provision have slightly different returns (during 2004-2005 the average difference was 0.77 percent per year).

Another problem with bond covenants is that some bonds have sinking funds provisions, where the issuing company can buy the bond back either in the market or at a pre-determined price prior to maturity. If the re-purchase is done on the market, it should only influence the liquidity of the bond, but if it can be re-purchased at a pre-determined price, it can cap the possible value of the bond, just like a call provision. There is no data on sinking funds in the bond data from Datastream.

The bond return series are naturally of different length. When the bonds are used to form portfolios, the portfolios will contain different numbers of bonds simply because there are not equally many AAA and BBB bonds available in the sample. Two final problems are i) matrix pricing[13] and ii) bonds registered under 144A. The matrix pricing is where some prices are calculated from dealer quotes. The matrix pricing might be a problem, but there is a month between prices, giving ample time for some trading to take place. There is trading reported in at least 14.5 percent of the observations. Furthermore the shorter sample window of 4.5 years gives a relatively large weight to short lived bonds where matrix pricing is a minor issue according to Sarig & Warga (1989). The bonds registered for 144A (private re-sale to institutions) can be in the sample twice. The reason for this is that the data consists of both the series for non 144A bonds and the series for 144A registered bonds. A bond that is registered as a 144A issue can have both a non 144A series and a 144A series. The over-all sample characteristics do not change if these 144A bond series are removed, so the series are kept to increase the cross-section.

The two factors not in focus, the interest rate risk and the liquidity risk, are controlled for in the estimation of default probabilities. A thin market is problematic with this equation since then variation over time can be allocated to the wrong time period and thus distort the parameter estimates. The remedy for this problem is to use a large cross-section, so that on average the returns are allocated to the correct time period. The interest risk control is the return spread for government bonds with seven years to maturity. Liquidity

[13]Datastream sources its corporate bond data from FT Interactive Data (FTID). FTID uses market transactions and calculates some prices using bid information from its fund clients. When prices are calculated, they reflect verifiable information to the extent that it is formative for the good faith opinion of FTID as to what a buyer would pay for the bond in a current sale, according to Thomson/Datastream.

factors explain part of corporate bond returns in other studies. In this study liquidity is merely a co-variation between return and turn-over. The control for the liquidity factor is the fairly crude average change in corporate bond traded volume. The liquidity control is calculated on traded volume from Datastream on the corporate bond sample.

Given that there are systematic effects in the sample, it is possible that these effects are already identified. Fama & French (1993) found that their small-minus-big (SMB), their term structure proxy, and their proxy for the corporate bond market factors were significant. The Fama and French high-minus-low (HML) factor was not so successful in explaining the returns. To help control for the effects found by Fama and French, the available factor series (SMB and HML) were downloaded from the home page of Kenneth R. French[14].

There are problems with the sample, for example as mentioned above matrix pricing, 144A and difference in size of the cross-section. In total the characteristics of the sample are what could be expected from a panel data set of corporate bonds.

1.5 Data treatment

The econometric model is based on the standard asset pricing test of Fama & MacBeth (1973). First the Fama and MacBeth method is used to see how well the CAPM based model can explain data. Even if the results are not striking, a second stage regression is used to extract the default risk from the different portfolios. The model can be used to extract the default risk in two ways. Both the beta equation (1.6)(p.31) and the CAPM equation (1.4)(p.30) are dependent on the default risk (π). The beta equation requires unobservable parameters, such as the expected value and variance of the stochastic discount factor (SDF), so the CAPM equation will be used for estimation purposes. The CAPM equation also contains several unknown parameters, but earlier studies can help in giving some guidance on what are reasonable proxies.

The beta can be estimated in a straight forward manner, since it is independent of market direction. The estimation of the market price of risk (λ) is more problematic since it reflects the average returns across portfolios. Typically very long time series are necessary to estimate the mean of λ.

Any return that is mean-variance efficient can be used to find the slope of the capital market line, which is the market price of risk. A market return proxy (R^m) is often used for this purpose. Assuming that the market return is

[14]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

mean-variance efficient, equation (1.3)(p.30) can be restated as a return beta representation. The return beta representation can then be used to estimate the parameters in;

$$E\left[r^{p}\right]=r^{f}+\beta\left(r^{m}-r^{f}\right) \tag{1.10}$$

Equation (1.1)(p.29) is based on the expected return and the SDF. These variables are not directly observable, so the realized returns will be used to extract information about them. Actual realized returns are used and not the common yield-to-maturity for par bonds or a spot rate curve based on zero-coupon yields until maturity. The information potentially in the term structure of the yields is lost when the realized returns are used. Shifts in the term structure can in this setting be systematic interest rate risk and this risk will be tested for using a set of maturity portfolios.

1.5.1 Portfolio formation

The final sample contains 6,045 U.S. corporate bond return series and to get a manageable system that can be tested using statistical standard methods the bonds are grouped into portfolios. The portfolio returns are formed by calculating the average log return (r) for each time period t.

$$r_t^{port}=\frac{1}{N_t}\sum_{j\in port} r_t^j, \tag{1.11}$$

where N_t is the number of bonds in the portfolio at time t and r_t^j is the return of bond j. The portfolios will contain an increasing number of bonds since there are more bonds available in later periods. The use of log returns and the formation into portfolios will decrease the impact of very high and very low returns.

The sample can be aggregated into many different portfolios, but the choice has been limited by data availability and to some extent by results from previous literature. The portfolio returns can also be considered to be returns from a naive $\frac{1}{N}$ portfolio allocation. Portfolios have been formed on S&P main ratings, FTSE/DJ industry classification benchmark, and time to maturity.

Debt rating is an indication of the quality of the debt, in the sense that it should convey information about the possibility of repayment. Two bonds in the same rating category should have more similar default probabilities than two bonds with different ratings. Another result of a successful implementation is that the default process can be observed in the ratings and ratings transitions tables. The S&P ratings are the long term bond ratings. Since the ratings change from time to time, the portfolio composition has been updated in January each year. In January a down-graded bond will belong to the new lower rating. Within each rating group there are "sub-ratings", i.e. there are 'AAA+' and 'AAA-'. These sub-ratings have been ignored, leaving twelve ratings portfolios, including the 'Not Rated' rating and the 'Not Available' where no S&P rating was found. Fama & French (1993) groups all non-investment grade bonds into one portfolio and Elton et al. (2001) eliminates low non-investment grade bonds from their sample. All main ratings are included here since one idea is that the default probability is increasing as the ratings indicate lower quality.

Firms belonging to the same industry can be expected to have similar operating risks, since they have similar inputs and are subject to the same regulation. Given similar operations, the firms could be expected to have similar default probabilities and recovery in default rates. The industry code used for forming portfolios was the FTSE/DJ Industry Classification Benchmark (ICB) hierarchy.[15] The highest level chosen provides ten industries categories. The industry classification code could be found for only about half the sample (48 percent) since the bond data contains no information on sectors. The company identifier in the ISIN code was used to identify the company and the industry classification could be found for the companies with listed equity in the sample.

The interest rate risk can be a systematic factor in bond pricing. The consequence of a shift in the interest level would impact longer maturity bond more than shorter ones. If the yield curve slope changes, then the impact might not show up as a systematic risk. Two options on controlling for the interest rate risk factor have been selected. First; a set of portfolios is formed based on maturities of the bonds; and second, a control variable for change in return spread is used in estimating the default probabilities. The choice of maturity as a portfolio determinant is problematic. Corporate bonds have shorter expected maturity and duration than stated maturity due to the default risk. However, using the duration calculated with the yield as weighting parameter sorts the bonds in almost the same way as the ratings based portfolios. To avoid the problem of 'actual duration', the maturity of the bonds is used to form portfolios.

[15] http://www.ftse.com/Indices/Industry_Classification_Benchmark

1.5.2 Beta calculation

According to (1.5)(p.30) the value of beta for a bond depends on the default probability. The beta is the co-variation between the return and a wealth portfolio. To implement the model the non-observable wealth portfolio will be substituted by a market portfolio. The proxy chosen for the remaining parts of the study is the return of the S&P 500 index.[16]

1.6 Results

In the next section, the existence of a systematic risk is examined. After this the recovery in default is examined to get an idea of the size that can be expected. Finally the default probabilities are extracted from the data set using the estimated systematic risk coefficients as a function of the recovery rate.

1.6.1 Estimation of systematic risk

This section on the systematic risk is divided into four subsections. First the beta is calculated for each bond in the sample, the large cross-section. After this the betas for three sets of portfolios are calculated (ratings, industry and maturity). Each section starts with a short motivation for the analysis and then the results are presented.

The cross-section

Earlier research has established that there is systematic risk in credit returns. The large number of bond return series give the opportunity not only to establish if there is systematic risk in the sample, but also to get a clearer picture of the distribution of systematic risk. Any bond with credit risk can default and thereby create a jump in it's return series. The 204 bond return series that default are both included and excluded, since they can be expected to influence the beta estimates.

The cross-section of the corporate bond sample is examined by first estimating parameters for individual bonds and then the pooled sample. The market price of risk (λ) is also calculated for the sample period. Given these estimates, it is possible to establish if there is systematic risk in the corporate

[16] Other indices that were considered were Dow Jones Industrial Average, the NASDAQ Composite, Russel 3000, and the Wilshire 5000. Neither one of these other indices gives any noticeable differences in size of parameter estimates or significance levels.

bond returns Values of α_j and β_j are estimated for each bond j in the cross-section using maximum-likelihood and ordinary least squares methods for the equation

$$r_{j,t} - r_t^f = \alpha_j + \beta_j \left(r_t^m - r_t^f \right) + \varepsilon_{j,t} \tag{1.12}$$

and the distribution plots for the beta estimates can be found in appendix 1.A. The data was then pooled and the alpha and beta were estimated for the entire sample and the two sub-samples of defaulted and non-defaulted bonds;

$$r_{j,t} - r_t^f = \alpha + \beta \left(r_t^m - r_t^f \right) + \varepsilon_{j,t} \tag{1.13}$$

For the pooled regressions there were a large number of non-existent data points. The data points were missing since bond trading starts at different points in time.[17] If the start of trading of the bonds is random then there is no systematic influence on the results, since if an observation is missing or not is random. If the estimate of alpha and beta vary over time, the relatively high number of data points late in the sample will influence the estimates more than the earlier points. In a second regression, the market price of risk (λ) was estimated in the cross-section using;

$$r_j - r^f = \lambda_0 + \lambda_1 \hat{\beta}_j + \nu_j, \tag{1.14}$$

where ν_j is the cross-sectional error term, and the average excess return is regressed against the estimated $\hat{\beta}_j$ with an intercept λ_0, to measure the market price of risk (λ_1).

The alpha and beta parameter estimates in Table 1.3 are significant for the pooled sample of 6,045 bond return series, both with and without the defaulted bonds in the sample. If the exclusion of ex-post defaulted bonds changes the parameter estimates, then the default risk influences the systematic risk.

[17] An alternative method instead of leaving out the missing data points would have been to balance the panel by replacing the missing data point with zero returns, but this would bias the coefficient estimates towards zero and give a false comfort as to significance testing.

Table 1.3. Estimated return beta representation for the pooled one factor model (monthly basis)

Homoscedastic error term	α		β		λ		R^2
Entire sample	-0.0021	***	0.0568	***	-0.0039	***	1.84%
	(0.0002)		(0.0055)		(0.0006)		
Defaulted bonds excluded	-0.0007	***	0.0387	***	-0.0043	***	7.10%
	(0.0001)		(0.0037)		(0.0006)		
Only defaulted Bonds	-0.0290	***	0.3239	***	-0.0026		21.76%
	(0.0036)		(0.0819)		(0.0031)		
GARCH(1,1) error term							
Entire sample	-0.0007	***	0.0855	***	-0.0047	***	1.47%
	(0.0001)		(0.0043)		(0.0006)		
Defaulted bonds excluded	-0.0009	***	0.0843	***	-0.0075	***	6.84%
	(0.0001)		(0.0028)		(0.0006)		
Only defaulted Bonds	0.0027		0.0857		0.0045		20.14%
	(0.0034)		(0.0777)		(0.0123)		

The α and β parameters have been estimated from a pooled sample as in equation (1.13) for the homoscedastic error term. The α and β for the heteroscedastic error term are the average ones for all the instruments in the respective sample. Standard errors within parentheses for α and β are calculated from a pooled sample estimate. The λ is estimated in a cross sectional regression on the estimated β coefficients. The standard error for λ is calculated using the Fama and MacBeth (1973) errors, as described in Cochrane (2001) chapter twelve. The R^2 measures are from the cross sectional calculation of the λ. ***, **, and * denotes significance on the 1, 5, and 10 percent level respectively.

The choice of error specification does not influence the sign on the parameter estimates, except for the defaulted bonds, but the magnitude of the parameters differs slightly. For the collection of defaulted bonds the GARCH(1,1) specification changes the estimated parameters. It could be expected that the alpha estimates should be close to or not significantly different from zero, since a large part of the bond portfolio (ex-post) does not default. The alpha can be interpreted as the expected return on a zero beta portfolio, or the return on a risk free instrument in the Black specification of the CAPM ($E[R] = E\left[R^{\beta=0}\right] + \beta\lambda$). Surprisingly the estimated alpha is negative for the entire sample and also when the defaulted bonds are excluded. For the defaulted bonds with GARCH(1,1) error terms, the estimated alpha is positive, but not significant. The negative sign of the estimated alpha means that after risk adjustment the corporate bonds have had lower return than the risk free rate during the sample period. In total, the corporate bonds did even worse than the proxy for the wealth portfolio. In unreported J-tests[18] the

[18] The J-test referred to is $J = \widehat{\alpha}' cov(\widehat{\alpha})^{-1} \widehat{\alpha} \sim \chi^2_{N-1}$,

where $cov(\widehat{\alpha}) = \frac{1}{T}\left[I - \beta(\beta'\beta)^{-1}\beta'\right] \sum \left[I - \beta(\beta'\beta)^{-1}\beta'\right]'$, and $\sum = E[\varepsilon_t \varepsilon_t']$. This formula is from chapter twelve in Cochrane (2001) as corrected in the errata. A more elaborate description can be found in Davidson & MacKinnon (1981). The estimations are difficult due to the large matrices ($6,045 \times 6,045$) for the largest one. Inversion of the largest matrices was not feasible, but for smaller sub-matrices ($1,000 \times 1,000$) the hypothesis of the α

null of the alpha of each instrument being jointly zero is strongly rejected for all tested sub-matrices. This is a bit problematic since the alpha should be zero if equation (1.10)(p.39) is a valid specification. The negative (and fairly large) alpha estimates invalidate the idea of equality between the expected return of a corporate bond and the risk free rate. It is slightly surprising that the rejection comes from the alpha estimates being lower than zero, but the negative alpha estimates are sufficient cause to reject the first claim. If there is systematic risk in the bond returns, there is more cause to reject the claim, so this is the next set of tests.

The beta estimates are the covariance between the corporate bond returns and the proxy for the wealth portfolio (S&P 500). The pooled sample estimate in Table 1.3, $\hat{\beta} = 0.0568$, indicates that the returns of corporate bonds vary positively with the market portfolio. However, it is only a very small part of the return that is explained by the covariance, indicating that the systematic market risk component plays a limited part in corporate bond returns over all. The simultaneous default event or other systematic risks in the large cross-section are thus either rare or not so costly. The estimated beta for defaulted bonds with homoscedastic error terms is relatively high, which is in line with the concept of risky bonds having similar characteristics as shares. When the GARCH error structure is used the estimated beta for the defaulted bonds is closer to the beta of the entire sample. The GARCH(1,1) does a good job in treating the large errors associated with the default event and thus the beta values produced by the GARCH structure are likely more representative for long-run corporate bond betas.

The estimates of the market price of risk ($\hat{\lambda}$) are significantly different from zero. The negative sign comes from the fact that the proxy for the wealth portfolio did poorly during the sample period. The R^2 values presented in Table 1.3 are low, implying that only a small portion of the returns can be explained in the model. Note also that the value for the GARCH specification seems slightly worse than the homoscedastic specification, but the error terms are slightly larger for the GARCH estimates by construction and this carries over into the calculation of the R^2.

The beta estimates are in the same neighborhood as the beta reported in Warner (1977) for railroad bonds during 1926 through 1930, but lower than the beta estimates calculated in Weinstein (1981). Note that the betas here are calculated using log returns and the studies other use simple returns. However, the evidence from the two studies indicates that betas vary over time. Weinstein also includes defaulted bonds in his calculations, but does not

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estimates being jointly zero could be safely rejected.

adjust for the possibility of GARCH errors, which seem to accompany default events. The results here are consistent with low and positive systematic risk for corporate bonds. Since the systematic risk is significant, no further functional forms are tested. It is conceivable that other functional forms could capture the systematic component even better.

The rating portfolios

Equation (1.6)(p.31) states that the systematic risk is a function of the default risk. Ratings are correlated with default rates, see for instance Moody's (2007). Lower quality ratings have higher default rates, so given the relationship specified in equation (1.6) higher beta value for lower quality rating can be expected.

The results from the ratings-based portfolios in Table 1.4 are insignificant, but suggests that the systematic risk varies with the rating of the bond. In Table 1.4 the systematic risks, as measured by the beta, are clustered into two groups, investment grade and non-investment grade. The fact that more bonds with lower credit quality default suggests that the relationship between the systematic risk and the rating is not just a correlation, but that the beta is a function of the rating.

The beta estimates are similar in size as the ones found by Berndt et al. (2006). The functional form of the error terms has less influence on the estimated portfolio betas than in the cross-section since the GMM[19] estimates are close to the GARCH estimates. It is natural that the difference between the standard OLS and the GARCH estimations is small, since the individual returns have much less impact on the parameter estimate for a portfolio of bonds.[20] The 'C' rating portfolio only consists of seven bonds but still has a significant coefficient.

[19] The Generalized Method of Moments; see Hansen (1982) for the details. The underlying idea is to find parameter values that minimize the moment conditions specified. Typically the moment conditions include the sum of the squared errors and orthogonality between the errors and the variables. The GMM framework allows for considerable flexibility, both in model specification and in hypothesis testing.

[20] There is considerable cross-sectional smoothing, especially if the shocks come at different times for different bonds. There were only three missing data points in the return series, and these were replaced by zero for the GMM estimates.

Table 1.4. Estimated return beta representation for the rating one factor model

	Homoscedastic error term				GARCH(1,1) error term			
Portfolio	α		β		α		β	
AAA	- 0.0015		- 0.0879	*	- 0.0015		- 0.0880	*
	(0.0024)		(0.0508)		(0.0024)		(0.0508)	
AA	0.0014		- 0.1302	**	0.0014		- 0.1304	**
	(0.0024)		(0.0563)		(0.0025)		(0.0563)	
A	0.0060	*	- 0.1052		0.0060	*	- 0.1055	
	(0.0034)		(0.0648)		(0.0035)		(0.0647)	
BBB	0.0010		- 0.0128		0.0010		- 0.0130	
	(0.0024)		(0.0604)		(0.0024)		(0.0598)	
BB	- 0.0066	**	0.1227		- 0.0066	**	0.1224	
	(0.0030)		(0.0747)		(0.0031)		(0.0748)	
B	- 0.0172	**	0.1366		- 0.0172	**	0.1360	
	(0.0071)		(0.1640)		(0.0072)		(0.1640)	
CCC	- 0.0206		0.1099		- 0.0205		0.1020	
	(0.0130)		(0.2480)		(0.0131)		(0.2495)	
CC	- 0.0065		0.1637		- 0.0040		0.1638	
	(0.0081)		(0.2290)		(0.0827)		(0.4763)	
C	- 0.0576	***	1.4823	**	- 0.0590	***	1.4679	**
	(0.0183)		(0.5693)		(0.0190)		(0.6307)	
D	- 0.0416		- 0.4892		- 0.0413		- 0.4901	
	(0.0269)		(0.4523)		(0.0268)		(0.4513)	
No Rating	- 0.0388	*	- 0.4956		- 0.0387	*	- 0.4963	
	(0.0218)		(0.4662)		(0.0218)		(0.4663)	
Not Available	- 0.0035		0.0192		- 0.0035		0.0188	
	(0.0038)		(0.0725)		(0.0038)		(0.0721)	
λ			- 0.0226				- 0.0238	
			(0.0194)				(0.0154)	
J			4 111				635	
R^2			37.64%				38.19%	

The α and β parameters have been estimated from the rating portfolios. For the homoscedastic error term the GMM method is used and for the GARCH(1,1) estimation a maximum Likelihood method. The standard errors for α and β are robust standard errors (White (1980)). The λ is estimated in a cross sectional regression on the estimated α and β coefficients. The standard error for λ is calculated using the Fama & MacBeth (1973) errors, as described in Cochrane (2001). The R^2 measures are from the cross sectional calculation of the λ. The J statistic is for testing if all pricing errors are jointly zero and is $\chi^2(11)$. ***, **, and * denotes significance on the 1, 5, and 10 percent level respectively.

The estimates with the homoscedastic error term in Table 1.4 for the ratings portfolios have been estimated using an iterated GMM method, where the inverse covariance matrix is used for weighting matrix. The results are very similar to the corresponding OLS estimates, but hypothesis testing is facilitated by using the GMM method (later in Table 1.5). There are more significant coefficient estimates than could be explained by chance alone, but primarily intercepts. There seems to be some systematic pattern in the estimates, the pricing errors ($\hat{\alpha}$) for investment grade debt (rating 'AAA' through 'BBB') are lower and positive than the non-investment grade (rating 'BB' through 'D') which has higher absolute values and are negative.

The investment grade (IG) and the non-investment grade (NIG) pricing errors ($\hat{\alpha}$) are tested independently using the Wald tests;

$$J_{IG} = \hat{\alpha}'_{IG} cov(\hat{\alpha}'_{IG})^{-1} \hat{\alpha}_{IG} = 26.53 \sim \chi^2(3), \; J_{NIG} = 15,398 \sim \chi^2(5),$$

where one degree of freedom is lost since the parameters are estimated. The null hypothesis of all pricing errors being zero can be rejected with more than 99.9 percent probability. The rating based portfolios have (negative) excess returns. There is a similar systematic form for the betas, where the investment grade betas are small and negative. The non-investment grade betas are large and positive. The beta results correspond well with the notion that the ratings agency (here S&P) manages to capture the risk of the bonds in their ratings. The reason for the systematic pattern in the betas might of course also be that the market trusts the ratings enough to price the bonds accordingly. Testing the hypothesis that beta values are different can be done with a Wald test.[21] The test is constructed as in equation (1.15) below;

$$\xi_W = \left[R\hat{\theta} - r\right]' V_{\hat{\theta}}^{-1} \left[R\hat{\theta} - r\right] \sim \chi^2(k), \tag{1.15}$$

where R is a matrix used for separating out the coefficient in the null hypothesis, $\hat{\theta}$ the estimated parameter values, r the value the coefficients should attain according to the null, and V_{θ}^{-1} the inverted covariance matrix of the parameters. The test statistic ξ_W is $\chi^2(k)$, where k is the number of restrictions.[22] Testing the null hypothesis that $\beta_k = \beta_j$ for $k, j = \{AAA, AA, ..., N/A\}$ shows in Table 1.5 that the null of different beta values cannot be rejected for some of the non-investment grade portfolios and the 'AAA' and the 'A' rated portfolios, but for all other combinations of ratings portfolios. The non-investment grade bonds tend to have similar beta values in the pair-wise testing.

[21] Wald tests are described in advanced econometric text books such as Ramanathan (1993).

[22] In a setting with two bonds rated 'AAA', and 'AA', the null hypothesis that $\beta_{AAA} = \beta_{AA}$ can be tested using $R = \begin{pmatrix} 1 & -1 \\ 0 & 0 \end{pmatrix}$, $\hat{\theta} = \left[\hat{\beta}_{AAA} \; \hat{\beta}_{AA}\right]'$, $r = [0 \; 0]'$. The test statistic in this case is $\xi_W = \left[(\hat{\beta}_{AAA} - \hat{\beta}_{AA} \quad 0)\right] (V_{\hat{\theta}})^{-1} \left[\begin{pmatrix} \hat{\beta}_{AAA} - \hat{\beta}_{AA} \\ 0 \end{pmatrix}\right] \sim \chi^2(1)$

Table 1.5. Pair wise testing of beta coefficients for the rating one factor model

	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Not Rated
AA	10.1										
A	1.7	7.6									
BBB	31.8	95.0	58.9								
BB	180.2	259.9	211.1	74.6							
B	96.8	136.8	112.3	42.9	0.4						
CCC	15.0	22.1	17.7	5.8	0.1	0.3					
CC	8.0	10.9	9.2	3.9	0.2	0.1	0.4				
C	66.6	70.2	68.1	60.4	49.9	48.9	50.9	46.9			
D	17.2	13.8	15.8	24.3	40.0	41.8	38.3	45.5	105.0		
Not Rated	22.7	18.3	20.9	31.9	52.3	54.7	50.2	55.0	105.6	0.0	
Not Available	64.6	269.7	224.2	7.0	43.5	26.5	3.2	2.6	57.8	27.6	36.3

The equivalence between betas is tested for different portfolios, and the test for the least difference is reported. The statistics are $\chi^2(2)$, since they are calculated using two restrictions. Any statistic above 6.0 represent a rejection at the 95 percent level.

A Wald test on the average betas for the investment grade bonds ($\bar{\beta}_{IG} = -0.08$) versus the average beta for the non-investment grade bonds ($\bar{\beta}_{NIG} = 0.25$) confirms that there is a significant difference ($\xi_W = 9,039 \sim \chi^2_{10}$).[23] There is a difference between (primarily) investment grade and non-investment grade debt betas.

The estimated market price of risk ($\hat{\lambda}$) is negative and lower for the ratings based portfolios (Table 1.4) than for the large cross-section (Table 1.3). This difference is an effect from the portfolio formation. Some portfolios contain a lot of bonds and some contain less, so the impact of a specific bond is different in the large cross-section and the portfolio sample. The estimated lambda is stable over estimation methods, and the reason for the large difference is the relatively higher weight in earlier periods for the ratings portfolios.[24] The R^2 values are fairly high, but again this only represents the portfolio structure and the ratings correlating with perceived risk (true or not).

The betas might be proxies for other risks. To eliminate two well known effects, the robustness of the results is tested using a three factor model. Two additional factors of Fama and French are used for second and third factors, i.e. the small-minus-big (SMB) and high-minus-low (HML). The results are presented in Table 1.B.1 in appendix 1.B. The beta estimates are slightly larger but similar. The investment grade and the non-investment grade bonds still have different market betas. The SMB factor does not add much in explaining the portfolio returns; none of the parameter estimates are significant. The

[23] If portfolios are formed on investment grade and non-investment grade status the beta estimates are -0.067 (0.043) and 0.197 (0.079) respectively.

[24] All ratings portfolios exist from the beginning of the sample, but the cross-section is much smaller in the beginning.

HML factors add explanatory power to the model.[25] The three factor model does not change the estimation of the market betas much. The addition of the SMB and the HML does not eliminate the systematic risk found in the one factor model. The high adjusted $\bar{R}^2$ indicates that the three factor model is superior in explaining the market price of risk (λ). Over all the results are consistent with the existence of a systematic risk factor for corporate bonds that co-varies with ratings.

The industry portfolios

Firms within the same industries face similar operational risks and have similar capitalizations on average and might thus have similar default risks and recovery rates on average. This idea can be confirmed if the systematic risk is significant in the industry portfolios. However, the industry based portfolios give much less guidance than the ratings based portfolios as to the systematic risk of the bonds as can be seen in Table 1.6. There are not more significant results than could be explained by chance alone.

[25] Both the SMB and HML factors increase the R^2 and the adjusted $\bar{R}^2$ when run as separate regressions.

Table 1.6. Estimated return beta representation for the industry one factor model

	Homoscedastic error term				GARCH(1,1) error term			
Portfolio	α		β		α		β	
Oil&Gas	0.0007		0.0608		0.0007		0.0611	
	(0.0028)		(0.0609)		(0.0028)		(0.0610)	
Basic Materials	0.0011		0.0004		0.0011		0.0006	
	(0.0020)		(0.0426)		(0.0020)		(0.0427)	
Industrials	-0.0000		-0.0390		-		-0.0387	
	(0.0021)		(0.0476)		(0.0022)		(0.0477)	
Consumer Goods	0.0005		0.0234		0.0005		0.0236	
	(0.0026)		(0.0430)		(0.0027)		(0.0430)	
Health Care	-0.0047		-0.1488		-0.0046		-0.1486	
	(0.0056)		(0.0914)		(0.0055)		(0.0914)	
Consumer Services	-0.0040		0.0327		-0.0040		0.0330	
	(0.0034)		(0.0712)		(0.0034)		(0.0714)	
Telecommunications	0.0010		0.2433	**	-0.0025	***	0.1454	***
	(0.0036)		(0.1028)		(0.0008)		(0.0168)	
Utilities	-0.0014		0.0441		-0.0014		0.0436	
	(0.0030)		(0.0826)		(0.0035)		(0.0871)	
Financials	-0.0131	**	-0.1002		-0.0130	**	-0.0999	
	(0.0055)		(0.1314)		(0.0058)		(0.1317)	
Technology	-0.0083		0.1004		- 0.0083		0.1006	
	(0.0051)		(0.0692)		(0.0051)		(0.0691)	
No ICBIC	-0.0055	**	0.0563		-0.0055	**	0.0566	
	(0.0025)		(0.0713)		(0.0025)		(0.0712)	
λ			0.0048				0.0070	
			(0.0212)				(0.0210)	
J			115				616	
R^2			28.25%				28.44%	

The α and β parameters have been estimated from the industry portfolios. For the homoscedastic error term the GMM method is used and for the GARCH(1,1) estimation a Maximum Likelihood method. The standard errors for α and β are calculated using the robust specification. The λ is estimated in a cross-sectional regression on the estimated α and β estimates. The standard error for λ is calculated using the Fama & MacBeth (1973) errors, as described in Cochrane (2001). The R^2 measures are from the cross sectional calculation of the λ. The J statistic is for testing if all pricing errors are jointly zero and is $\chi^2(10)$. ***, **, and * denotes significance on the 1, 5, and 10 percent level respectively.

Table 1.6 was generated using the same set of equations as Table 1.4, but the bond sample is arranged according to industry rather than ratings. The fact that the market price of risk (λ) is positive, but not significant does not really mean much in light of the earlier results. However, the explained variation is surprisingly high considering the non-significant parameter estimates with an R^2 of 28 percent. The pricing errors are jointly different from zero. The individual parameter estimates cannot be significantly separated from zero.

Table 1.7. Pair wise testing of beta coefficients for the industry one factor model

	Oil& Gas	Basic Mat.	Indu-strials	Cons. goods	Health Care	Cons. Serv.	Tele-comm.	Util-ities	Fin.	Tech.
Basic Materials	26.8									
Industrials	73.1	20.7								
Consumer Goods	10.3	6.9	50.8							
Health Care	163.4	82.8	44.8	110.3						
Consumer Serv.	3.2	4.3	21.1	0.4	122.5					
Telecomm.	13.9	24.6	33.2	20.1	64.0	18.5				
Utilities	0.3	2.1	7.7	0.5	41.6	0.1	16.5			
Financials	8.5	3.3	1.2	5.0	0.8	5.8	38.6	6.8		
Technology	2.6	16.4	31.8	9.7	101.7	7.5	8.5	3.5	13.2	
No ICBIC	0.1	18.2	52.7	6.3	156.4	2.3	14.6	0.2	8.0	3.2

The equivalence between betas is tested for different portfolios, and the test for the least difference is reported. The statistics are $\chi^2(2)$, since they are calculated using two restrictions. Any statistic above 6.0 represent a rejection at the 95 percent level. Note that the industry names have been abbreviated in some cases.

A Wald test similar to the rating portfolios is shown in Table 1.7. The results give some guidance on the beta values found in the sample. The consumer services, the utilities, and the financial industries can only occasionally be separated from the other industries. However for the other industries, there are marked differences. For example, it would be erroneous to use the 'health care beta' to value a bond from an oil&gas company.

The robustness of the estimates is tested using the three factor model of Fama and French. The results are presented in Table 1.B.2 in appendix 1.B. The industry portfolios did show a marked difference between the one and three factor model. Two portfolios had a large change in their market beta and this is consistent with the industry having risk characteristics that were captured by the SMB and the HML factors. However the significance is still poor for the parameters of the industry portfolios. Similarly to the ratings portfolios, the SMB factor seems to have a smaller impact than the HML factor. Including the HML factor increases the R^2 in the second pass regression. Adding the SMB factor decreases the $\bar{R}^2$. The adjusted $\bar{R}^2$ is not as large, but the variations in the lambda are well explained.

In total the industry betas have some informational content on the systematic risk for corporate bonds, but much less so than the ratings based portfolios.

The maturity portfolios

A change in the interest rate level impacts the value of all bonds. It is thus conceivable that the explanation for the systematic risk in the cross-section is the impact of changing interest rates. Bonds with different maturities can be expected to have different sensitivities against interest rate risk, simply because the payment structures are different. A one year bond and a two year bond are not equally sensitive to a change in the discount rate.

Table 1.8. Estimated return beta representation for the maturity one factor model

	Homoscedastic error term			GARCH(1,1) error term			
Portfolio	α		β	α		β	
-1 year	-0.0040	**	-0.0484	-0.0040	**	-0.0484	
	(0.0017)		(0.0457)	(0.0017)		(0.0457)	
1 -2 years	-0.0049	***	0.0155	-0.0049	***	0.0155	
	(0.0014)		(0.0376)	(0.0014)		(0.0376)	
2-5 years	-0.0086	**	0.0347	-0.0086	**	0.0347	
	(0.0036)		(0.0782)	(0.0035)		(0.0781)	
5-10 years	-0.0021		0.0610	-0.0021		0.0610	
	(0.0023)		(0.0603)	(0.0023)		(0.0604)	
10-15 years	-0.0002		-0.0174	-0.0002		-0.0174	
	(0.0031)		(0.0707)	(0.0031)		(0.0713)	
15-20 years	0.0004		0.0849	0.0001		0.0803	**
	(0.0030)		(0.0729)	(0.0031)		(0.0287)	
20 years -	0.0013		0.0101	0.0013		0.0101	
	(0.0030)		(0.0589)	(0.0031)		(0.0601)	
λ			-0.0204			-0.0216	
			(0.0396)			(0.0373)	
J			216			321	
R^2			25.94%			26.03%	

The α and β parameters have been estimated from the maturity portfolios. For the homoscedastic error term the GMM method is used and for the GARCH(1,1) estimation a Maximum Likelihood method. The standard errors for α and β are calculated using the robust specification. The λ is estimated in a cross sectional regression on the estimated α and β estimates. The standard error for lambda is calculated using the Fama and MacBeth(1973) errors, as described in Cochrane (2001). The R^2 measures are from the cross sectional calculation of the λ. The J statistic is for testing if all pricing errors are jointly zero and is $\chi^2(6)$. ***, **, and * denotes significance on the 1, 5, and 10 percent level respectively.

Longer time to maturity gives a higher opportunity cost if the interest rate changes, since it is carried for a longer time. A longer bond is thus more sensitive to changes in interest rate risk, but a longer bond might also be more susceptible to other risks, such as default risk. A one year bond is exposed to the one-year-default risk and a two year bond is exposed to this risk *and* the two-year-default risk. Both these ideas would indicate an increasing beta in the maturity based sample.

The maturity based portfolios give no clear-cut answer to whether the systematic risk depends on the time to maturity of the bonds, as can be seen in Table 1.8. Shorter time to maturity tends to have a lower systematic risk, but the coefficients are not significant. The only coefficients that are significant are the shorter maturity intercepts, indicating that there has been poor performance in these bonds during the sample period.

Table 1.8 was generated using the same set of regressions as the earlier tables, but with the sample arranged in maturity portfolios. Again the estimated market price of risk is not credible as a proxy for what the investors ex-ante expected. The R^2 is in line with the industry portfolios, and the cross-sectional variation is only explained in part. Again the pricing errors ($\hat{\alpha}$) are jointly different from zero. The choice of estimation method has very little impact on the estimated parameters and their standard errors.

Table 1.9. Pair wise testing of beta coefficients for the maturity one factor model

	-1 Year	1-2 Years	2-5 Years	5-10 Years	10-15 Years	15-20 Years
1-2 Years	15.3					
2-5 Years	21.5	1.1				
5-10 Years	45.0	16.6	2.2			
10-15 Years	3.6	6.5	8.4	37.1		
15-20 Years	66.8	21.7	7.9	2.6	46.9	
- 20 Years	12.2	0.1	1.9	9.2	2.7	19.9

The test for equivalence between betas for different portfolios, where the test for the least difference is reported. The statistics are $\chi^2(2)$, since they are calculated using two restrictions. Any statistic above 6.0 represent a rejection at the 95 percent level.

In Table 1.9 the same Wald test was calculated as for the earlier portfolios. The beta, or systematic risk, for the longest time to maturity portfolio (20+) is the one most difficult to separate from the others. This non-separation is most likely due to the low sensitivity to the market portfolio; the beta is close to zero. The difference between the betas is not as large, so choosing the wrong beta is of no importance in a valuation situation.

The three factor model does add some power for the maturity portfolios; see Table 1.B.3 in appendix 1.B. The three factor model makes two market betas significant, and as for the earlier portfolios the HML factor contributes significantly.[26] Primarily the shorter maturity portfolios are better described by the three factor model indicating that the model adds something for shorter time horizons. The HML factor is difficult to interpret, since it could be a proxy for some type of risk, for instance the default risk. The three factor model increases the adjusted $\bar{R}^2$ substantially for the cross-sectional regression.

The weak pattern in systematic risk might be due to the interest rate risk or difference in default risk over maturity. These two factors cannot be separated using the data here. The fact that the estimates are insignificant suggests that the interest rate risk is at a minimum not a major explanatory factor for the existence of the systematic risk.

Is there systematic risk?

All corporations operate under some risks, hence their debt is risky in some sense. The message from the previous sections is that corporate bonds in general not only have individual risks, but also exhibit low positive systematic

[26] Adding only the HML factor gives an increase in the R^2 to 33 percent, but a decrease in the $\bar{R}^2$ to 20 percent

risk. The evidence also supports a correlation between rating and size of systematic risk. This makes intuitive sense and suggests that; lower grade bonds will tend to have simultaneous defaults more often than higher grade bonds. That is, lower grade bond returns have higher covariance with the market portfolio returns than the returns for higher grade bonds. There might be other systematic risks as well, such as shift in the yield curve, even if this particular proposition is not supported by the evidence from the maturity based portfolios in Table 1.8. This example of an additional systematic risk should impact the returns of investment grade and non-investment grade bonds equally. There is a substantial difference in systematic risk if the bond is investment grade or not. This indicates that the default risk is a more likely explanation than the shift in the yield curve. It would have been natural to suspect that external shocks would influence companies in the same industry in similar ways. Perhaps somewhat surprisingly, it does not seem like the industry classification is very important. In total, the conclusion is that the data and the results conform to the findings of Weinstein (1981). The first claim can be rejected for two reasons, i) the average excess return is significant and negative, as seen in the estimates of alpha and ii) there is a systematic component to the corporate bonds returns, as seen in the estimates of beta.

1.6.2 Estimating the loss in default

The loss in default (γ) has to be estimated, to be able to calculate the default probability, since these two variables jointly determine the beta according to the specification in equation (1.6)(p.31). From Moody's (2005) special comment, the average recovery rate for all corporate bonds from 1982 to 2003 is 42.2 percent and the recovery rate for 2004 is 54.3 percent. It would be reasonable to expect investors to anticipate a recovery rate in this range.

The lowest simple net return[27] during a month was calculated for all the defaulted bonds. The use of simple returns in this section facilitates the comparison with Moody's figures on loss in default. The average of the lowest simple returns was -52 percent indicating that this is the return in the default month, when it is known or highly probable that the company will default on the bond, i.e. if USD 100 was invested in a bond the month preceding the default, only USD 48 would be left after the market price had been adjusted for the default. The 48 percent remaining after default could be interpreted as the market's expectation of the recovery rate, in line with the estimation from Moody's.[28] If the recovery rate is assumed constant during the time

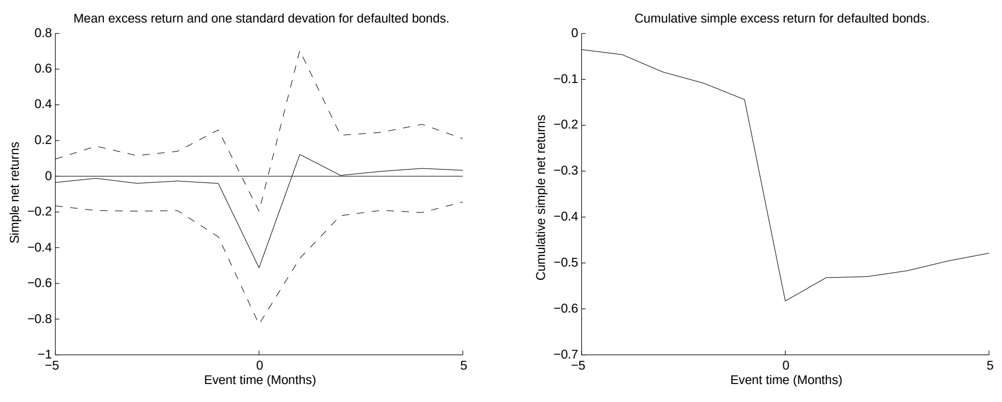
[27] The simple net return is the return calculated as $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$.

[28] Moody's base their recovery rate on 30-day post default bid prices if available. If there

period, then it would be one approximation of the market's expectations for the recovery rate.

A more careful examination confirms that the simple point estimate from Moody's is a fairly good approximation. The main concern is if the concept of a one time hit is a good approximation of the price process after default or not. If the approximation is not a good approximation, then the model with a one time pay-off in default is not valid without more adjustments. If there is a string of poor returns following the default event, then the recovery in default needs to be adjusted for the process after default. This is particularly important if the defaulted bond is illiquid, since there might be no way of avoiding the returns post-default. Note that the data for the defaulted bonds have a low quality; there are several bonds that are virtually without value. If a worthless bond gets a small up-tick in price it will register as a high return. One bond was eliminated from the defaulted bonds sample for this reason (it was worth about 0.1 percent of face value and had returns in the order of 900 percent). In the figure below, it can be seen that the defaulted bonds tended to have worse excess returns for some months prior to the default, and slightly higher excess returns after the default event. In Figure 1.1 below the excess return is the return on the defaulted bonds minus the average return for the entire sample.

Figure 1.1 Excess return on defaulted corporate bonds 2001-2005.



In the first period after the default event, there is an up-tick, and this might be an indication of an overshooting effect. There might be a problem with

are no post default prices available, then trading prices two weeks preceding the default are used.

stale prices, but there is better price information immediately after default than before. A simple event study method is used to estimate the returns at default;

$$R_{j,t} - \bar{R}_t = \delta D_{prior} + \zeta D_{default} + \theta D_{post} + \eta_{j,t}, \tag{1.16}$$

where $R_{j,t}$ is the return of the defaulted bond j, $\bar{R}$ the average return of the entire bond sample, D_{prior}, is a dummy variable that take on the value one if time t is before the event, $D_{default}$ is another dummy variable that take on the value one if t is the default time period, and D_{post} is the post default dummy variable and it takes on the value one if t is after the default event. For each time period and each bond, the sum of the D variables is one. Different windows were tested, but the estimations were similar for all the windows. The estimated coefficient value for the prior dummy (δ) was -0.027 with standard error in parenthesis (0.0058), for the default dummy (ζ) it was -0.510 (0.0222), and for the post-default dummy (θ) it was 0.045 (0.0111). It seems like there is a process where bonds that are about to default are performing worse than the market in total. The largest loss comes when the default event either occurs or is known by the market. These results indicate that using a point estimate for the loss in default is a fair approximation for the purposes of this paper. It is clear that the instantaneous loss is not followed by a similarly large loss in the month after the default, so the second claim can be (at least) weakly refuted.

1.6.3 Estimating default probabilities

With the estimates of beta and the loss in default (γ) it is possible to estimate the default probabilities, by running a second pass regression. This second pass regression is similar to the second pass regression used in Fama & MacBeth (1973), but instead of calculating the market price of risk (λ) the default probabilities are calculated. To do this equation (1.4)(p.30) can be re-written as;

$$r^p_{t+1} = \frac{r^f_{t+1} + \hat{\alpha}_j + \hat{\beta}_j \lambda_{t+1}}{(\pi_j \gamma + (1 - \pi_j))} + \eta_{j,t+1}, \tag{1.17}$$

where the estimated parameters from equation (1.12)(p.42) are used. Each portfolio has a single default risk (π_j) that is assumed to be fixed over time, and the new second pass error term is $\eta_{j,t+1}$. The choice to include the estimated alpha is not obvious. From CAPM there is no role for the estimated alpha and it should thus be zero, but if it is not included then the fit of the estimation deteriorates, since the realized returns both for the market portfolio and the different bond portfolios are poor. The idea behind the second regression (1.17) is that there is information not used in the first run that can be used to find the idiosyncratic default probabilities. The estimations of π from equation (1.17) should be cautiously interpreted, since there is an underlying assumption that the realized returns are consistent with the promised returns.

The default probabilities are used in determining the beta, so the results for π_j can be expected to be somewhat weak. Most of the information in the systematic default probabilities, the covariance with the SDF, is used to determine the beta. Another interpretation of equation (1.17) is that the expected value of return in the numerator needs to be scaled using the default probabilities to match the promised return, and the scaling factor depends on the recovery in default and the default probability.

The system of moment conditions that are necessary to solve in order to find the default risk is not linear, so numerical methods are used to extract the default probabilities. The estimates are calculated using a range of values on the market price of risk, since the negative in-sample estimates hardly are representative of the investors' ex-ante expectations. It is important to note that the solutions found in estimating the default probabilities are not necessarily global optimums. The estimates can thus vary a bit depending on what solution is found by the estimation procedure.

Table 1.10.a Estimated monthly default probabilities

γ	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	NR	N/A
	$\lambda =$	2%										
40%	0.33%	0.13%	0.22%	0.00%	0.25%	0.00%	0.67%	0.00%	0.56%	2.63%	2.31%	0.28%
50%	0.38%	0.16%	0.26%	0.00%	0.36%	0.00%	0.80%	0.00%	0.67%	3.15%	2.77%	0.35%
60%	0.48%	0.19%	0.34%	0.00%	0.37%	0.00%	1.00%	0.00%	0.83%	3.95%	3.46%	0.43%
	$\lambda =$	3%										
40%	0.34%	0.15%	0.26%	0.39%	0.00%	0.00%	0.62%	0.00%	0.37%	2.70%	2.32%	0.00%
50%	0.41%	0.18%	0.31%	0.46%	0.00%	0.00%	0.74%	0.00%	0.44%	3.23%	2.79%	0.00%
60%	0.50%	0.22%	0.36%	0.00%	0.34%	0.00%	0.98%	0.00%	0.53%	4.05%	3.57%	0.42%
	$\lambda =$	4%										
40%	0.36%	0.17%	0.27%	0.38%	0.00%	0.00%	0.60%	0.00%	0.17%	2.76%	2.39%	0.00%
50%	0.48%	0.29%	0.49%	0.53%	0.00%	0.00%	0.75%	0.00%	0.22%	4.02%	2.89%	0.40%
60%	0.52%	0.25%	0.39%	0.00%	0.31%	0.00%	0.96%	0.00%	0.23%	4.16%	3.67%	0.42%
	$\lambda =$	5%										
40%	0.36%	0.18%	0.27%	0.00%	0.20%	0.00%	0.62%	0.00%	0.00%	2.84%	2.52%	0.29%
50%	0.41%	0.21%	0.39%	0.00%	0.00%	0.00%	0.76%	0.00%	0.00%	3.37%	3.09%	0.35%
60%	0.53%	0.28%	0.41%	0.00%	0.29%	0.00%	0.94%	0.00%	0.00%	4.26%	3.77%	0.42%
	$\lambda =$	6%										
40%	0.37%	0.21%	0.29%	0.00%	0.20%	0.00%	0.61%	0.00%	0.00%	2.91%	2.58%	0.31%
50%	0.45%	0.25%	0.35%	0.00%	0.25%	0.00%	0.73%	0.00%	0.00%	3.49%	3.10%	0.35%
60%	0.55%	0.31%	0.44%	0.00%	0.27%	0.00%	0.91%	0.00%	0.00%	4.36%	3.88%	0.43%

The default probabilities are estimated using GMM from the predicted values of the first pass beta estimation and different values for the market price of risk (λ) and recovery rate (γ). The probabilities were constrained from below by zero. The market price of risk is given as a yearly rate.

The estimates are calculated with the market price of risk ranging between two and six percent on a yearly basis. Since the recovery rate is uncertain and might vary for different ratings, the default probability is extracted as a function of the recovery rate in Table 1.10a above. The default probabilities are restricted to be positive in the calculations.

The estimated monthly default probabilities without controls are generally very high in comparison to the actual default rate of the sample, 0.06 percent per month.[29] Even so, the results are in many cases consistent in the sense that a worse (lower grade) rating gives a higher default probability. There are two bond portfolios with only zero probabilities indicating that either there are no positive probabilities or that there is not idiosyncratic risk left. The estimates have different sensitivity to the recovery rate (γ) where lower rated bonds exhibit larger differences in estimation when the recovery rate changes. The 'not rated' portfolio seems to be treated much like very low grade rated bonds, indicating that investors consider them of poor quality. The reason for this is that the 'not rated' label is given to bond issues that have been rated and where the issuing companies have declined further ratings coverage. The bonds where no ratings were available (N/A) exhibited quite low default probabilities. It is thus better to have no label than to be assigned the 'not rated' label by S&P.

[29] 204 bonds defaulted out of a total of 6,045 in the sample during 54 months.

Table 1.10.b Estimated monthly default probabilities with controls for yield curve changes and liquidity

γ	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	NR	N/A
	$\lambda=$	2%										
40%	0.02%	0.03%	0.39%	0.01%	0.05%	0.63%	1.10%	0.07%	0.00%	0.01%	0.00%	0.32%
50%	0.07%	0.10%	1.76%	0.11%	0.00%	1.04%	1.11%	0.12%	0.00%	0.02%	0.00%	0.53%
60%	0.00%	0.15%	0.00%	0.00%	0.00%	0.00%	2.36%	0.00%	0.00%	0.00%	0.01%	0.00%
	$\lambda=$	3%										
40%	0.01%	0.00%	0.26%	0.01%	0.00%	0.48%	1.18%	0.00%	0.00%	0.00%	0.00%	0.12%
50%	0.06%	0.03%	0.10%	0.70%	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.12%
60%	0.10%	0.02%	0.08%	0.87%	0.88%	0.17%	0.77%	0.53%	0.00%	0.01%	0.06%	0.00%
	$\lambda=$	4%										
40%	0.01%	0.08%	0.16%	0.01%	0.07%	0.39%	1.11%	0.00%	0.00%	0.00%	0.00%	0.10%
50%	0.00%	0.05%	0.69%	0.13%	0.00%	0.13%	1.02%	0.00%	0.00%	0.00%	0.00%	0.04%
60%	0.02%	0.18%	0.08%	0.15%	0.01%	0.00%	2.49%	0.00%	0.00%	0.00%	0.46%	0.00%
	$\lambda=$	5%										
40%	0.00%	0.00%	0.13%	0.02%	0.00%	0.39%	1.08%	0.00%	0.00%	0.00%	0.00%	0.08%
50%	0.00%	0.00%	0.49%	0.07%	0.00%	0.25%	1.26%	0.00%	0.00%	0.00%	0.00%	0.00%
60%	0.00%	0.05%	0.12%	0.33%	0.03%	0.00%	1.99%	0.02%	0.00%	0.00%	0.43%	0.00%
	$\lambda=$	6%										
40%	0.00%	0.01%	0.52%	0.08%	0.00%	0.44%	0.92%	0.00%	0.00%	0.00%	0.00%	0.04%
50%	0.00%	0.06%	1.35%	0.30%	0.00%	0.48%	0.70%	0.00%	0.00%	0.00%	0.01%	0.13%
60%	0.00%	0.13%	0.84%	0.96%	0.05%	0.01%	1.84%	0.00%	0.00%	0.00%	0.01%	0.01%

The default probabilities are estimated using GMM from the predicted values of the first pass beta estimation and different values for the market price of risk (λ) and recovery rate (γ). The probabilities were constrained from below by zero. The market price of risk is given as a yearly rate.

The estimated default probabilities decrease, as they should with more degrees of freedom, for most portfolios when controls for changes in the yield curve and liquidity are added. The crude controls for the yield curve (The US Government bond return spread for a seven year bond (γ_y)) and liquidity (average change in reported corporate bond traded volume (γ_l)) are added onto equation (1.17),

$$R_{t+1} = \frac{R^f_{t+1} + \hat{\alpha}_j + \hat{\beta}_j \lambda_{t+1}}{(\pi_j \gamma + (1 - \pi_j))} + \gamma_l C_{Liquidity} + \gamma_y C_{Yieldcurve} + \eta_{j,t+1}. \qquad (1.18)$$

The idiosyncratic risk is thus not only dependent on default risk, but also interest and liquidity risks, as measured by the controls. Contrary to what could be expected, the lower grade bonds have no or limited default risk, and the higher grade bonds have high default rates compared to the sample average. The same calculations on the sample divided into industry and maturity portfolios are presented in Appendix 1.B.

1.6.4 About default probabilities

The systematic risk component seems to have at least the three commonly suggested factors (default, interest rate and liquidity risk). This result is in line with for instance Chen et al. (2005) who found that their liquidity measure could explain a fair part of variation in yield spread, both for investment grade and non-investment grade bonds. De Jong & Driessen (2005) finds that their sample of corporate bonds have significant exposure to equity market liquidity and treasury bond market liquidity factors. In total there is evidence that corporate bonds have exposure to liquidity and this is also picked up by the crude factor used here. The finer point here is that given the systematic risk, which seems to be related to the default risk, there is also an idiosyncratic default risk after the controls for yield curve shifts and liquidity have been added.

The estimated default probabilities are extracted from the returns of corporate bonds. If the controls used here are proxies for something else than expected, the results are weaker. The slightly too high estimates of the remaining idiosyncratic default risk can be interpreted in terms of yield spreads. If investors have a higher probability of default than actual default rates in their trading, the observable yield spreads will also be larger than could have been expected. The higher estimates of the default probabilities can also help to explain the high yield spreads for corporate against government bonds (yield spread puzzle). If the investors indeed have the higher default probabilities in their pricing than motivated by default rates, the spread will as a result be larger.

The results regarding the third claim are a bit mixed. On the one hand there are problems both with the estimation and to some extent the results. On the other hand, the results can be interpreted as a systematic and idiosyncratic default risk with important roles for yield curve shifts and liquidity. In total there is support for the third claim, but there is more to it than default risk.

1.7 Conclusion

The estimated beta values in Table 1.3 (p. 43) support the claim that there is a systematic influence of default risk on bond returns. The explanatory value of the CAPM based model is, as is common for these models, not very strong for many of the portfolios. In the large cross-section there is a marked difference depending on if the defaulted bonds are included or not. The difference is almost eliminated for the betas when the GARCH specification is used. The investment grade bonds have marginally significant negative beta values and this is consistent with their default risks having a negative covariance with the market return. The negative beta means that the investment grade bonds earn positive returns when market returns are negative. This result is consistent with the concept of 'flight to quality', meaning that investors increase the price they are willing to pay for safe assets when markets have negative returns. The reverse story is true for non-investment grade bonds. The critical dividing point is the investment grade status, where the difference between the two groups is significant. The actual grading within these two groups tends to have much less of an impact, i.e. the systematic risk of a 'BB' rated bond is more like a 'CCC' bond than a 'BBB' bond.

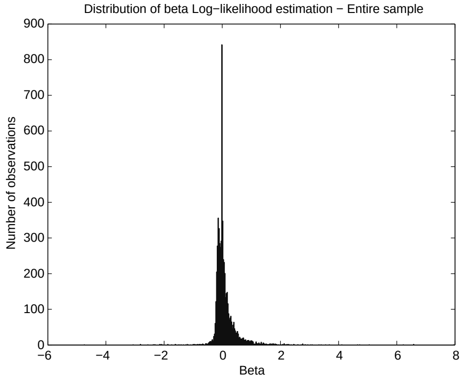
There is evidence for the importance of the default risk also as an idiosyncratic risk. Together with the yield curve shift control and liquidity control, the estimated default probabilities are closer to what can be expected from the average actual default rate than without the controls. The importance for the liquidity in corporate bond pricing has been established in earlier studies and this study adds to this evidence. The role for default risk both as a systematic and an idiosyncratic risk is new. For the systematic part the results of Weinstein (1981) are essentially confirmed, there is in general a low positive systematic risk in the sample with regards to the proxy for the wealth portfolio. Also the results of Fama & French (1993) are in a sense confirmed, since they use two term structure return factors and the default risk explains the average returns. Unlike Fama and French, the support for equal long-term expected return for corporate and government bonds is non-existent. In fact the higher beta estimates from the GARCH estimates indicate that the traditional calculation of beta might be systematically too low for single bond estimates. If this is true, then corporate bonds might have too low betas and therefore not generate sufficient returns for their risk.

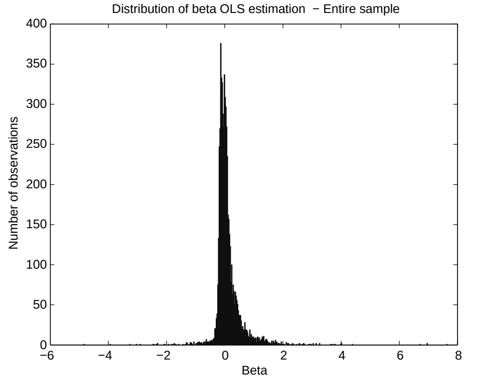
The bonds that went into default in the sample did have a poor performance for some time preceding the default, but the large impact came in the event month. After the initial loss given that default was de facto known, the bonds tended to have a small positive abnormal return and there was a small over-shooting effect. Overall the difference between using a point estimate and using a longer period to calculate the loss-in-default is not so large.

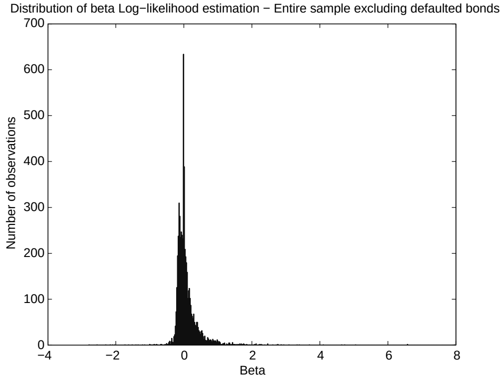
The estimated default probabilities are high before the controls. After the controls have been introduced, the estimated default probabilities are still high, but not completely out of line with actual default rates. The default risk is important for the idiosyncratic risk in the tests, even if the liquidity measure is the larger factor, since its inclusion decreases the estimated default probabilities by a factor of up to ten. The CDS results of Berndt et al. (2006) are not directly comparable, but they find that 35 percent of the variation in firm-specific default risk premia can be explained by a latent common component (they refer to it as firm specific default risk premium factor).

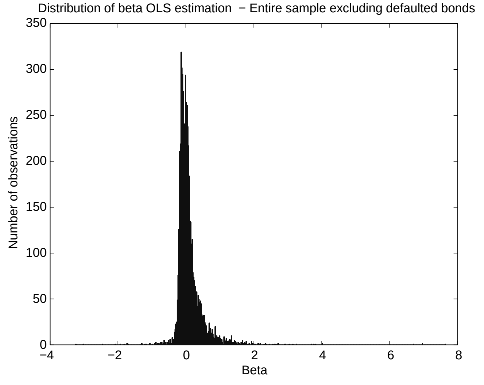
The evidence for default risk and its association with the return of corporate bonds is strong, even if there are more factors at work. The default risk influences the pricing of corporate bonds both in expected cash-flows and in the required return. The expected payment depends directly on the default risk, and the discount factor should be adjusted in accordance with the systematic risk to correctly price a corporate bond.

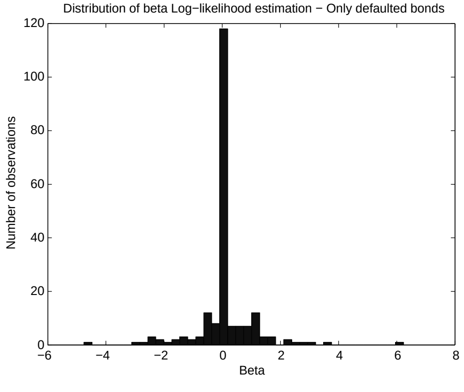
1.A Appendix - Beta histograms

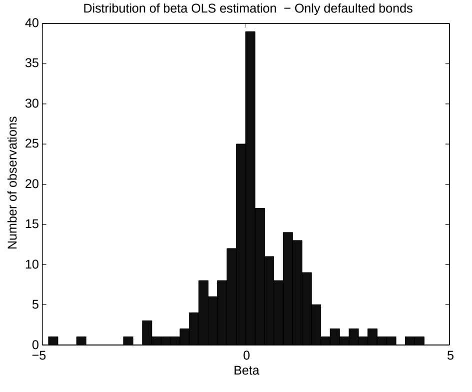












1.B Appendix - Three factor model tables

Table 1.B.1. Estimated return beta representation for the ratings three factor model

Portfolio	α		Market β		SMB	HML	
AAA	-0.0023		-0.1182	**	0.1242	-0.0363	
	(0.0024)		(0.0467)		(0.0923)	(0.0666)	
AA	0.0008		-0.1212	**	0.0343	0.0428	
	(0.0028)		(0.0502)		(0.1002)	(0.0881)	
A	0.0063	*	-0.0727		-0.0846	0.0611	
	(0.0037)		(0.0542)		(0.1382)	(0.1082)	
BBB	-0.0002		0.0283		0.0154	0.1305	
	(0.0026)		(0.0665)		(0.0824)	(0.0838)	
BB	-0.0097	***	0.2320	***	0.0303	0.3417	***
	(0.0030)		(0.0585)		(0.0891)	(0.0898)	
B	-0.0223	***	0.4222	***	-0.1397	0.7967	***
	(0.0072)		(0.1399)		(0.2983)	(0.2822)	
CCC	-0.0245	**	0.4199	**	-0.2844	0.8070	
	(0.0122)		(0.1900)		(0.5494)	(0.6359)	
CC	-0.0109		0.1257		0.4101	0.0671	
	(0.0095)		(0.1930)		(0.2505)	(0.3440)	
C	-0.0766	***	2.0203	***	0.4816	1.8268	***
	(0.0205)		(0.5443)		(0.6941)	(0.6065)	
D	-0.0434	*	0.1358		- 1.0433	1.4199	
	(0.0247)		(0.4238)		(1.1995)	(1.2956)	
Not Rated	-0.0486	**	0.1138		-0.3897	1.6595	*
	(0.0228)		(0.3463)		(0.8618)	(0.9728)	
Not Available	-0.0056		0.1368	**	-0.0584	0.3279	**
	(0.0039)		(0.0600)		(0.1298)	(0.1456)	
λ			-0.0118		0.0026	-0.0213	
			(0.0138)		(0.0106)	(0.0102)	
J						619	
R^2						95.57%	
$\bar{R}^2$						94.59%	

The α and β parameters have been estimated from the rating portfolios using the GMM method. The standard errors for αs and βs are calculated using the robust specification. The λs are estimated in a cross-sectional regression on the estimated αs and βs. The standard errors for λs are calculated using the Fama and MacBeth (1973) errors, as described in Cochrane(2001) chapter twelve. The R^2 measures are from the cross-sectional calculation of the λ. with no intercept. The J statistic is for testing if all pricing errors are jointly zero and is $\chi^2(11)$. ***, **, and * denotes significance on the 1, 5, and 10 percent level respectively.

Table 1.B.2. Estimated return beta representation for the industry three factor model

Portfolio	α		Market β		SMB	HML	
Oil&Gas	-0.0006		0.0548		0.1176	0.0324	
	(0.0029)		(0.0595)		(0.1064)	(0.0946)	
Basic Materials	-		0.0218		0.0427	0.0820	
	(0.0022)		(0.0424)		(0.0742)	(0.0828)	
Industrials	-0.0012		-0.0092		0.0363	0.1044	
	(0.0022)		(0.0501)		(0.0787)	(0.0744)	
Consumer Goods	-0.0004		0.0094		0.0982	0.0001	
	(0.0027)		(0.0443)		(0.1002)	(0.0924)	
Health Care	-0.0055		-0.0202		-0.1765	0.3077	
	(0.0051)		(0.0818)		(0.2477)	(0.2858)	
Consumer Services	-0.0068	**	0.1477	**	0.0038	0.3454	**
	(0.0033)		(0.0649)		(0.1355)	(0.1461)	
Telecommunications	0.0019		0.2833	**	-0.1477	0.0551	
	(0.0038)		(0.1202)		(0.1236)	(0.1068)	
Utilities	-0.0042		0.0981		0.1250	0.2152	*
	(0.0034)		(0.0770)		(0.1037)	(0.1155)	
Financials	-0.0169	***	0.0149		0.0876	0.3818	
	(0.0056)		(0.0995)		(0.1974)	(0.2720)	
Technology	-0.0111	*	0.2324	***	-0.0330	0.3804	**
	(0.0059)		(0.0742)		(0.1045)	(0.1647)	
No ICBIC	-0.0085	***	0.1369	**	0.0871	0.2788	***
	(0.0024)		(0.0623)		(0.0704)	(0.0795)	
λ			0.0051		-0.0012	-0.0211	
			(0.0153)		(0.0119)	(0.0107)	
J						378	
R2						62.64%	
$\bar{R}^2$						53.30%	

The α and β parameters have been estimated from the industry portfolios using the GMM method. The standard errors for the αs and the βs are calculated using the robust specification. The λs are estimated in a cross-sectional regression on the estimated αs and βs. The standard errors for the λs are calculated using the Fama and MacBeth (1973) errors, as described in Cochrane (2001) chapter twelve. The R^2 measures are from the cross-sectional calculation of the λs. with no intercept. The J statistic is for testing if all pricing errors are jointly zero and is $\chi^2(10)$. ***, **, and * denotes significance on the 1, 5, and 10 percent level respectively.

Table 1.B.3. Estimated return beta representation for the maturity three factor model

Portfolio	α		Market β		SMB		HML	
-1 Year	-0.0053	***	-0.0032		0.0115		0.1406	**
	(0.0016)		(0.0515)		(0.0424)		(0.0491)	
1-2 Years	-0.0061	***	0.0564		0.0186		0.1308	**
	(0.0014)		(0.0361)		(0.0369)		(0.0440)	
2-5 Years	-0.0118	***	0.1720	**	-0.0105		0.4067	**
	(0.0032)		(0.0609)		(0.1324)		(0.1518)	
5-10 Years	-0.0047	*	0.0932	*	0.1440	*	0.1596	**
	(0.0023)		(0.0500)		(0.0776)		(0.0715)	
10-15 Years	-0.0033		0.0499		0.1168		0.2526	**
	(0.0031)		(0.0628)		(0.0966)		(0.0989)	
15-20 Years	-0.0023		0.1026		0.1857	*	0.1341	
	(0.0029)		(0.0686)		(0.0989)		(0.0882)	
- 20 Years	-		0.0483		0.0287		0.1269	
	(0.0032)		(0.0631)		(0.1053)		(0.0991)	
λ			-0.0204		0.0211		-0.0127	
			(0.0292)		(0.0156)		(0.0156)	
J							403	
R^2							65.73%	
$\bar{R}^2$							48.60%	

The α and β parameters have been estimated from the maturity portfolios using the GMM method. The standard errors for the αs and the βs are calculated using the robust specification. The λs are estimated in a cross-sectional regression on the estimated αs and βs. The standard errors for the λs are calculated using the Fama and MacBeth (1973) errors, as described in Cochrane(2001) chapter twelve. The R^2 measures are from the cross-sectional calculation of the λs. with no intercept. The J statistic is for testing if all pricing errors are jointly zero and is $\chi^2(6)$. ***, **, and * denotes significance on the 1, 5, and 10 percent level respectively.

1.C Appendix - Default risk, industry and maturity

The method used to generate the default probabilities for the ratings portfolios is also applied to the industry portfolios. The market price of risk and the recovery in default are also varied in the same range.

Table 1.C.1. Estimated monthly default probabilities

γ	Oil& Gas	Basic Mat.	Indu- strials	Cons. goods	Health Care	Consu. Serv.	Tele- comm.	Util- ities	Finan- cials	Tech- nology	No ICBIC
	$\lambda =$	2%									
40%	0.00%	0.65%	0.91%	0.86%	1.64%	1.23%	0.40%	1.12%	2.84%	0.66%	0.00%
50%	0.00%	0.78%	1.09%	1.03%	1.97%	1.48%	0.48%	1.35%	3.41%	0.79%	0.00%
60%	0.00%	0.98%	1.36%	1.29%	2.46%	1.85%	0.60%	1.68%	4.27%	0.98%	0.00%
	$\lambda =$	3%									
40%	0.00%	0.66%	0.91%	0.86%	1.66%	1.24%	0.37%	1.12%	2.87%	0.65%	0.00%
50%	0.00%	0.79%	1.10%	1.03%	2.00%	1.48%	0.44%	1.35%	3.44%	0.78%	0.00%
60%	0.00%	0.99%	1.37%	1.29%	2.50%	1.86%	0.55%	1.68%	4.30%	0.98%	0.00%
	$\lambda =$	4%									
40%	0.00%	0.66%	0.92%	0.86%	1.68%	1.24%	0.34%	1.12%	2.89%	0.65%	0.00%
50%	0.00%	0.80%	1.11%	1.03%	2.02%	1.49%	0.41%	1.35%	3.47%	0.78%	0.00%
60%	0.00%	1.00%	1.39%	1.29%	2.53%	1.86%	0.51%	1.68%	4.34%	0.98%	0.00%
	$\lambda =$	5%									
40%	0.00%	0.67%	0.93%	0.86%	1.71%	1.25%	0.32%	1.12%	2.92%	0.65%	0.00%
50%	0.00%	0.80%	1.12%	1.03%	2.05%	1.50%	0.38%	1.35%	3.50%	0.78%	0.00%
60%	0.00%	1.01%	1.40%	1.29%	2.56%	1.87%	0.47%	1.68%	4.38%	0.97%	0.00%
	$\lambda =$	6%									
40%	0.00%	0.68%	0.94%	0.86%	1.73%	1.25%	0.29%	1.12%	2.94%	0.65%	0.00%
50%	0.00%	0.81%	1.13%	1.03%	2.07%	1.50%	0.35%	1.35%	3.53%	0.77%	0.00%
60%	0.00%	1.01%	1.41%	1.29%	2.59%	1.88%	0.43%	1.68%	4.41%	0.97%	0.00%

The default probabilities are estimated using GMM from the predicted values of the first pass beta estimation and different values for the market price of risk (λ) and recovery rate (γ). The probabilities were constrained from below by zero. Note that the industry names have been abbreviated in some cases. The market price of risk is given as a yearly rate.

The industry based portfolios exhibit even larger default probabilities than the ratings based portfolios, indicating that they are much more heterogeneous in their risk profile. Note that the industry portfolios contains only about half of the number of bonds compared to the ratings based portfolios (for exact number of bonds see Table 1.2). Also fairly safe industries, such as utilities and basic materials have fairly high default probability estimates. Only two portfolios, the Oil&Gas and the No ICBIC, have zero default probabilities. The results support the notion that the model does not do very well on the industry based portfolios, just as for the industry beta values.

The impact of changing the market price of risk (λ) seems to be negligible for quite a few portfolios, i.e. there is almost the same default risk with different market price of risk. The default probability seems to be more sensitive towards the recovery ratio (γ), since the estimated probability changes a fair amount when the recovery rate is varied.

Table 1.C.2. Estimated monthly default probabilities with controls for yield curve changes and liquidity

γ	Oil& Gas	Basic Mat.	Indu-strials	Cons. goods	Health Care	Consu. Serv.	Tele-comm.	Util-ities	Finan-cials	Tech-nology	No ICBIC
	$\lambda =$	2%									
40%	0.00%	0.05%	0.03%	0.08%	0.15%	0.08%	0.06%	0.01%	0.96%	0.12%	0.00%
50%	0.00%	0.10%	0.05%	0.13%	0.76%	0.20%	0.15%	0.00%	2.49%	0.53%	0.00%
60%	0.00%	0.11%	0.08%	0.17%	0.91%	0.18%	0.18%	0.00%	3.13%	0.78%	0.00%
	$\lambda =$	3%									
40%	0.00%	0.02%	0.03%	0.07%	0.09%	0.04%	0.00%	0.11%	1.01%	0.06%	0.00%
50%	0.00%	0.00%	0.12%	0.12%	0.32%	0.05%	0.01%	0.35%	2.55%	0.07%	0.00%
60%	0.00%	0.02%	0.16%	0.16%	0.49%	0.06%	0.07%	0.53%	3.17%	0.13%	0.00%
	$\lambda =$	4%									
40%	0.00%	0.03%	0.06%	0.06%	0.09%	0.01%	0.01%	0.04%	1.12%	0.01%	0.00%
50%	0.01%	0.02%	0.17%	0.04%	0.29%	0.01%	0.00%	0.19%	2.63%	0.11%	0.00%
60%	0.00%	0.03%	0.23%	0.13%	1.05%	0.07%	0.07%	0.96%	3.29%	0.66%	0.00%
	$\lambda =$	5%									
40%	0.02%	0.04%	0.02%	0.07%	0.13%	0.04%	0.00%	0.04%	1.12%	0.04%	0.00%
50%	0.05%	0.05%	0.00%	0.09%	0.67%	0.05%	0.00%	0.31%	1.91%	0.30%	0.00%
60%	0.00%	0.02%	0.03%	0.15%	1.33%	0.02%	0.00%	0.62%	2.95%	0.64%	0.00%
	$\lambda =$	6%									
40%	0.04%	0.02%	0.00%	0.07%	0.05%	0.04%	0.03%	0.18%	0.74%	0.07%	0.02%
50%	0.00%	0.01%	0.02%	0.12%	0.39%	0.04%	0.00%	0.21%	2.84%	0.05%	0.00%
60%	0.03%	0.00%	0.04%	0.15%	0.82%	0.00%	0.03%	0.25%	3.55%	0.47%	0.00%

The default probabilities are estimated using GMM from the predicted values of the first pass beta estimation and different values for the market price of risk (λ) and recovery rate (γ). The probabilities were constrained from below by zero. Note that the industry names have been abbreviated in some cases. The market price of risk is given as a yearly rate.

Adding a control for shifts in the yield curve and liquidity lowers the estimates. The probabilities are, with the exception of 'Financials', close to the mean observed level in the sample. The impact of the two variables is smaller in absolute terms after the controls are introduced. Changing the market price of risk does not change the estimates of default risk much, in most cases. The changes in parameter estimates are smaller in absolute term when the recovery rate is varied. The estimated default risks are close to what could have been expected if the sample had been actual default risks, i.e. measured as defaulted bond divided by total number of bonds issued. The idiosyncratic risk is much better described when controls are present, indicating that the controls are important.

The method used to generate the default probabilities for the ratings and the industry portfolios is also applied to the maturity portfolios. The market price of risk and the recovery in default are also varied in the same range.

The results from the estimation without controls are not reported. Only three portfolios (2-5 years, 10-15 years, and -20 years) have estimated default probabilities that differ from zero.

The estimated default probabilities are too few to really interpret before the controls are added. The fairly long term 10-15 year bonds deviates from the others in having a fairly high default probability. Disregarding the 10-15 years portfolio there seems to be no major differences in default risk for the different portfolios.

Table 1.C.3. Estimated monthly default probabilities with controls for yield curve changes and liquidity

γ	-1 Year	1-2 Years	2-5 Years	5-10 Years	10-15 Years	15-20 Years	-20 Years
	$\lambda =$	2%					
40%	0.11%	0.10%	0.00%	0.02%	0.20%	0.02%	0.03%
50%	0.14%	0.17%	0.00%	0.01%	0.29%	0.01%	0.09%
60%	0.07%	0.06%	0.00%	0.00%	0.92%	0.00%	0.29%
	$\lambda =$	3%					
40%	0.22%	0.12%	0.00%	0.06%	0.58%	0.00%	0.08%
50%	0.19%	0.13%	0.00%	0.00%	0.22%	0.10%	0.42%
60%	0.29%	0.07%	0.00%	0.00%	1.01%	0.00%	0.60%
	$\lambda =$	4%					
40%	0.24%	0.12%	0.00%	0.00%	0.32%	0.08%	0.00%
50%	0.33%	0.15%	0.00%	0.01%	0.82%	0.22%	0.13%
60%	0.10%	0.13%	0.00%	0.02%	0.42%	0.14%	0.44%
	$\lambda =$	5%					
40%	0.17%	0.11%	0.00%	0.08%	0.35%	0.04%	0.14%
50%	0.23%	0.09%	0.01%	0.05%	0.79%	0.08%	0.31%
60%	0.42%	0.17%	0.00%	0.07%	1.05%	0.03%	0.44%
	$\lambda =$	6%					
40%	0.31%	0.11%	0.00%	0.01%	0.13%	0.01%	0.04%
50%	0.38%	0.13%	0.00%	0.00%	0.81%	0.01%	0.19%
60%	0.36%	0.22%	0.00%	0.00%	0.05%	0.01%	0.48%

The default probabilities are estimated using GMM from the predicted values of the first pass beta estimation and different values for the market price of risk (λ) and recovery rate (γ). The probabilities were constrained from below by zero. The market price of risk is given as a yearly rate.

All the estimates are ten times larger than what could be expected from actual default rates before the controls are added. Clearly the control for yield curve shifts and liquidity are important since the estimated default risks decrease to credible levels when the controls are added.

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Chapter 2

Returns to Defaulted Corporate Bonds

Abstract

I test for short term excess return in a sample of 279 defaulted US corporate bonds using multiple regression analysis. There are robust excess returns after controlling for market and liquidity risk. The expected recovery rate during 2001-2006 is estimated to be, on average, four percentage points lower the first month after default than the present value of the recovery rate after nine months.

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2.1 Introduction

The measurement of the recovery rate helps to determine the value of bonds for going concerns. The value of a bond is the present value of the future payments, so a biased estimation of the recovery rate will bias pricing of bonds after, but also before a default. If the recovery rate is biased, it can influence the post default returns if the bond price corrects to its intrinsic value. The value of a bond depends on the future possible states. For a risky bond the recovery rate is a possible future state, making the value of the recovery rate important also before default.

There are reasons to believe that trading is imperfect for defaulted bonds and that recovery rates might be depressed. First, some of the empirically noted results for non-defaulted bonds can survive (liquidity, default risk, and interest rate risk), or even be exacerbated at a default. Second, the market for defaulted securities can exhibit information asymmetries.

The pricing of non-defaulted corporate bonds is influenced by liquidity. Ericsson & Reneby (2003) find that bond spreads incorporate a substantial liquidity component in addition to the default risk. The less liquid a bond is in the study of Chen et al. (2005) the higher the yield spread, and De Jong & Driessen (2005) find that liquidity is a priced factor in a multi-factor model. If corporate bond prices are sensitive to liquidity before default, there is no reason to think that they are less sensitive after default. The systematic part of the default risk is priced (see Weinstein (1981), Berndt et al. (2006) or the previous chapter in this thesis). If the market beta is a measure of the default risk, it can be expected to increase after default. The co-variation with the market return is higher when the asset is closer to being equity. The interest rate risk is ignored here, since it is not likely a major contributor to the risk of a defaulted corporate bond.

In a default situation for a company there are new reasons for trading the securities. Some investors, such as pension funds and insurance companies, are not allowed to hold high risk assets. Other investors specialize in this type of high risk asset. This specialization could potentially create a situation of information asymmetry.[1] The existence of vulture funds indicates there are opportunities to earn good returns on distressed or defaulted assets.

Both the liquidity factor and the asymmetric information after a default event can bias the estimate of the recovery rate downwards. In general non-defaulted bonds have high probabilities of debt service and thus fairly small

[1]Financial organizations that specialize in distressed securities, such as near default or defaulted bonds or shares, are commonly referred to as vulture funds.

variations in their expected pay-off space. The holders of defaulted corporate bonds have to find some means of knowing what their bonds are worth. A natural choice is to look at what has been recovered in earlier defaults, making the historic recovery rates the norm also for future recovery rates. The cross-sectional studies of recovery rates started with Altman & Kishore (1996). Recovery rates are now studied by the rating agencies as a matter of routine (cf. Moody's (2007)). Altman & Kishore (1996) shows that industry and the seniority of a bond matters for the recovery rate in the cross-section. They cannot show that investment grade status, size of issue, or longevity before default has any impact on the recovery rate. The frequent studies of the cross-section can be self fulfilling, but should not influence a possible bias. That is, any pre-existing bias can be strengthened by the success of the cross-sectional studies since it is the only information available on recovery rates.

There are three common ways of defining the recovery rate of defaulted bonds in the literature:

- Recovery of the face value of the bond,
- recovery of market value preceding the default, or
- an equivalent, but default-free, bond.

These three methods are all based on an instant change into a safe asset. If there are unlimited trading opportunities the three methods are equivalent. If it is not possible to immediately realize the bond, then the variation in the recovery rate of the bond is important for the economic value of a defaulted bond. The recovery rate of face value is the market price one month after default of the bond divided by the face value, and the recovery rate of market value is the market price one month after default of the bond divided by the market price one month before the default.

There are two issues that can generate variability in the recovery rate; post default risk and information asymmetry between investors. Altman & Pompeii (2003) show that the market value divided by the face value of defaulted bonds varies from 0.15 to 0.74 and differs from year to year. The bonds in their sample are the defaulted bonds that are included in the Altman-NYU Salomon Center Defaulted Bond Index. Corporate bonds typically do not have a well functioning secondary markets, so it is plausible that variation in recovery rates can have an impact on bond prices.

There are a few possible ways to figure out if there is a systematic bias in the cross-sectional default rates:

- the repayments from defaulted bonds could be summed and discounted for a net present value,
- the returns from vulture funds could be tested for excess returns, or
- the return on bonds of defaulted firms could be tested for excess returns.

The repayments from defaulted firms are difficult to study since the data are typically not public and it often takes a long time until the default is resolved and/or bankruptcy is finalized. The main problem with studying vulture funds is that there is a collection of assets in the funds at any time. Some of these assets might be recently defaulted bonds, but there can be many other assets as well. The vulture managers may add value to the defaulted securities after default and such a study can be biased to increase the value of the assets at default. I study the return on bonds[2] of companies that have defaulted on their securities for a limited number of months after default. There are two reasons for studying a short time period after default. First, it takes time to do value enhancing restructurings, and second, it is possible that the recovery rate is depressed by a larger than usual supply just after default.

The underlying claim that is tested in this study is straight forward;

Claim 2.1 *The market price of a defaulted bond is biased*

Multiple regression analysis is used to test the claim that the one month recovery rate estimation is biased. I confirm cross-sectional results from Moody's (2007), and introduce time-series tests on defaulted corporate bond returns. The risk factors used to explain the excess returns do not in fact explain the returns. This implies that there is mispricing for defaulted bond returns. Neither the common liquidity nor the Fama & French (1993) factors have any strong bearing on the excess return after default. The estimated recovery rates ares four percent too low on average to make the excess return go away during 2001-2006.

In the next section, the rationale for the asset pricing tests are described. In section 2.3 the tests and calculations that deviate from standard asset pricing tests are presented. The summary statistics of the sample and how the sample selection was done is described in section 2.4. The results are presented and discussed in section 2.5. Concluding remarks are presented in section 2.6.

[2] The implicit assumption here, as in most models of the default rate, is that the priority rule is strictly enforced. The owners of equity get nothing until the bond owners are fully reimbursed. In reality this is not typically the case. Weiss (1990) finds that in 27 cases out of 37 the priority rule is not strictly enforced.

2.2 Intensity model of corporate bond value

The purpose of this section is 1) to explain how the default value of the bond relates to the before default value and 2) to describe how the bond value can be compared over periods after default. The value of the bond (V) at time t is equal to the discounted present value of the expected value of the bond value at date $t+1$.

$$V_t = e^{-r_t} E\left[V_{t+1} + C_{t+1}\right] \tag{2.1}$$

For simplicity assume that the coupon is zero here ($C_{t+1} = 0$). The default arrival intensity for a bond is (λ).[3] The default intensity can be thought of as expected defaults per time unit. Assume that the default intensity is exogenous in this model. The model in equation (2.1) is in discrete time, so the default probability is the sum of the default intensity process over the time period:

$$\pi_{t,t+1} = e^{-\int_t^{t+1} \lambda_s ds} \tag{2.2}$$

Define the value of the bond at time $t+1$ as V_{t+1}^d for the default state and V_{t+1}^s in the survival state. The value of the default state is the recovery value. The survival value of the bond is ultimately the promised payment. The states of default or survival are mutually exclusive, so equation (2.1) can be decomposed into:

$$V_t = e^{-r_t} \left(E\left[\pi_{t,t+1} V_{t+1}^d\right] + E\left[(1-\pi_{t,t+1}) V_{t+1}^s\right] \right) \tag{2.3}$$

The default probability of a safe bond is by definition $\pi_{t,T} = 0$ and the safe bond value at maturity (T) is thus equal to its face value $V_T = 1$. The payment in default is the object of interest, so define the payment in default function as $\delta : f_{t+1} \rightarrow V_{t+1}^d$. The set of factors f_{t+1} contain all information necessary to determine the payment in default (V_{t+1}^d). δ can be seen as the time-varying exchange rate between the promised payment and the payment at default, so $\delta\left(f_{t+1}\right) \leq V_{t+1}^s$. Assuming a constant probability of default (π) gives the valuation formula at time t before default τ ($t < \tau$):

$$V_t = \pi e^{-r_t} E\left[\delta(f_{t+1})\right] + (1-\pi) e^{-r_t} E\left[V_{t+1}^s\right] \tag{2.4}$$

and after default $t > \tau$:

$$V_t = e^{-r_t} E\left[\delta(f_{t+1})\right] \tag{2.5}$$

[3]For a discussion on default intensity, see for instance Duffie & Singleton (2003) section 3.4.

Assume that creditors take over when a company defaults on its debt payments. This implies that the company is then free of all debt and there cannot be any additional defaults. Since I study only a short time after default, this should not influence the results.

There are three standard ways to define the default payment function; recovery of face value of the bond $\delta(f_{t+1}) = k_1$, recovery of market value $\delta(f_{t+1}) = k_2 V_t$, and recovery in a safe bond $\delta(f_{t+1}) = k_3 V^s_{t+1}$, where k_1, k_2 and k_3 are constants. In the recovery of a safe bond an investor receives a fraction (k_3) of a safe bond that otherwise has the same characteristics as the defaulted bond.

If liquidity is poor after default, a bond owner is exposed to the variability of the asset price and an unknown holding period. This can result in changing values of the recovery rate and a simple test of this is

$$\delta(f_{t+1}) = \frac{\delta(f_{t+q})}{\prod_{i=t+1}^{t+1+q}(1+\rho_i)}, \tag{2.6}$$

where q is the number of time periods after default, and ρ_i the discount rate. I use the risk adjusted discount rate in a Capital Asset Pricing Model (CAPM) setting, as can bee seen in equation (2.10 p. 81). The value of the bond at default depends on the return on the asset $\delta(f_{t+1})$ function and the holding period q.

There are two ways to calculate the recovery rate from equations (2.4) and (2.5). The recovery rate can be calculated before and after the default. It is much simpler to calculate the recovery rate after default since there are less parameters to estimate.

2.3 Test method

First the recovery rates are calculated for each year for seniority and industry groups. These calculations are done so to align with earlier research on recovery rates. The default time is not when the bond issuer formally defaulted on the obligation, but the time when the market adapted the bond price to include the certain future default of the firm on the interest or principal.[4] In practice this means that the largest negative price adjustment for each time series is defined as the default period. After default equity factors can be expected to play a larger role in explaining the expected returns and therefore

[4]The price adjustment occurs when investors realize that the company will not be able to service the debt. The actual default date is the date the service is due.

market, liquidity, Small-Minus-Big (SMB) and High-Minus-Low (HML) are tested.

All returns are measured excluding the accrued interest. Only in cases where the bond is repaid in full does this exclusion matter. This is not common for defaulted bonds, so the impact on my results should be minimal. All tests have also been done also with returns including the accrued interest. The difference in results are minimal and if anything the inclusion of the accrued interest increases the excess return and risk adjusted discounted recovery rate.

2.3.1 Cross-section

The cross-sectional recovery rates are calculated to enhance the comparability with for instance Moody's (2007). The cross-sectional calculations are sample means, and can be described in OLS terms as,

$$\delta_{\tau,i} = \alpha_\tau + \beta f_\tau + \epsilon_{\tau,i}, \tag{2.7}$$

where
$\delta_{\tau,i}$: the recovery rate for bond i at default time τ,
f_τ: dummies for the estimated groups, and
ϵ_τ: error term for bond i.

The subscript τ is there to indicate that it is only calculated at the time of default. To get the mean of a specific group simply add the intercept (α_τ) and the group beta (β). The intercept is the average recovery rate and the beta is the impact of any specific industry, or seniority. The regressions are run for the entire sample and for each year. Altman & Kishore (1996) has shown that the recovery rates tend to vary from year to year.

2.3.2 Time-series

Second, I want to see if there is any excess return in defaulted bonds. The idea is to find out if the defaulted bonds have returns that exceed their risk compensation. A defaulted bond can be seen as something that is between debt or equity, since the true status typically is unknown at the time of default. This unknown status implies that either factors important for corporate bond pricing or equity pricing might be useful in risk adjusting the defaulted bond returns.

Factors that have been found to influence corporate bond pricing in earlier studies are tested for my sample of defaulted bonds. This means for the defaulted bonds that I test for a CAPM market risk factor (β_m) and liquidity risk factors (β_l). The market risk factor can be expected to increase in significance after the default simply from the bond taking on a more equity like pay-off profile. The earlier tests are complemented with testing for liquidity risk in defaulted bonds, and construct bond liquidity factor series in Section 2.4.1. In addition to the test of bond factors I test factors from Fama & French (1992) which have been successful in explaining equity returns. Aside from the market factor, Fama and French calculates the Small-Minus-Big (SMB) and High-Minus-Low (HML) factors from a set of portfolios. The SMB factor is a company size factor and the HML is a valuation factor (shares are ranked on book-to-market).

The statistical models used to test for significance of factors are standard portfolio tests, with portfolio formation dependent on industry and seniority. The estimation equation can be seen in equation (2.8),

$$R_t - R_t^f = \alpha + \beta F_t + \epsilon_t, \tag{2.8}$$

here R_t is the simple return on a bond at time t, R^f is the risk free return, F_t is a vector of factors, and ϵ_t is the error term. The intercept (α) is the mean unexplained difference between the bond return and the risk free rate, and the beta is the vector of covariances between the bond return and the factors in F_t. A significant beta estimate signals that the factor helps to explain the difference between the bond return and the risk free rate. All tested factors are not zero cost portfolios. This implies that for the non zero cost portfolios the average value of the factors can influence the estimated intercept, and hence the estimated excess return.

The portfolios are equally weighted, since the market capitalization cannot be determined from my data set. Studies on equity portfolios use typically use value-weighted portfolios. The choice of equally weighted portfolios can give smaller issue bonds a relative large impact on the results.

2.3.3 Present value of recovery rates

To estimate the economic significance of the post default variations in the recovery rate, the present value of the recovery rate of face value (market price of the bonds divided by their face value) after default is calculated. The interest rate for market risk is adjusted to see if the estimate for $\delta_{\tau+n}$ over time differs from the "at default" recovery rates for both book and market values. The discounting is presented below in equation (2.10).

Defaulted bonds are assets which need to generate risk adjusted returns for investors to hold them. There should be an insignificant excess return (alpha) and insignificant betas if the use of a risk free asset as a proxy for the recovery value is a good assessment. The variability in price of the safe asset is by nature small, and the default probability is also small (empirically fractions of percent per month). If the value in default is too depressed, then there should be excess returns in the months following the default. These excess returns are the fingerprints of the too low recovery rate. The sample is randomly divided into two groups to avoid discounting with in-sample betas. The first group is used to calculate betas for industry and seniority,

$$R_t^j - R_t^f = \alpha_j + \beta_j F_t + \epsilon_t, \tag{2.9}$$

where R_t^j is the return on bond j at time t, R_t^f is the risk free return, F_t is a vector of factors, and ϵ_t is the error term. Time (t) runs from the time of default (τ) for k periods. The coefficient estimates are used for calculating the discount rate in the next equation.

The second group is used to calculate the out-of-sample present value of the equivalent recovery rate of face value ($RR = \frac{CleanPrice}{FaceValue}$). This operation is done to make the recovery rates comparable over time. Note that the excess return test is sufficient to answer the question of bias in the recovery rate at default. The present value of the recovery rates is calculated as,

$$PV(RR_{\tau+n}) = \frac{RR_{\tau+n}}{\prod_{i=\tau}^{\tau+n}(1 + R_i^f + \hat{\beta}F_i)}, \tag{2.10}$$

where alpha is assumed to be zero and beta ($\hat{\beta}$) is the mean estimated parameter from the first group estimated in accordance with equation (2.9). Equation (2.10) is used to calculate the present value up to nine months after default (n). The reason for this relatively short period is that the recovery rate might be depressed at the time of default, not that there is a drift in the asset value. Each bond is assigned a post-default beta in accordance with what grouping it belongs to.

2.4 Data

The sample consists of 134 companies with 279 defaulted bond price series. The sample is collected from the Thomson/Datastream database. All bonds in the sample have fixed coupons. The sample period covers six years from 2001 to the end of 2006.

A problem with corporate bond data is typically thin trading. For the average bond in the Datastream sample, trade volume is registered in the

ISMA TRAX system in 14 percent of all months. The average traded volume (nominal) for a traded bond is 7.8 MUSD per month. The traded volume is on average about 264 MSUD per month in the sample. The median bond issue has an amount issued of 200 MUSD.[5]

Datastream does not only rely on the TRAX system for price information, but mainly source their corporate bond data from FT Interactive Data (FTID). FTID uses market transactions and calculates prices using, amongst other things, bid information from their fund clients. According to FTID; prices are calculated to reflect verifiable information to the extent that it is formative for the good faith opinion of FTID as to what a buyer would pay for the bond in a current sale.

The price information has a tendency to go stale after the default, i.e. the same price is repeated during several time periods in the data set. If there is a problem with stale prices, the intercepts in the CAPM tests are negative since there is a financing cost (R^f), but no income from the bond. The default event seems to create volume. I compare the average turn-over five months before default to five months after default. The sample after default has 24 percent higher turn-over, measured in term of face value. Using the, potentially, stale prices in an asset pricing study favors finding no positive excess return, or lower discounted recovery rates.

Summary statistics for the sample of defaulted bond are presented in Table 2.1.

[5]ISMA (the International Securities Market Association) is the self-regulatory organization and trade association for the international securities market (including the Eurobond market). ISMA TRAX is the ISMA trade matching and regulatory reporting system for the OTC markets.

Table 2.1. Monthly sample returns during ten month before default and ten months after default.

Asset	Observations	Mean	Std dev	Skewness	Kurtosis	Min	Max
Entire sample	279	-0.00	0.34	39.86	2316.62	-1.00	24.00
Senior Secured	29	-0.00	0.11	-0.46	36.79	-1.00	0.95
Senior Unsecured	113	-0.00	0.41	43.52	2380.52	-1.00	24.00
Senior Subordinated	52	-0.00	0.41	23.99	752.48	-0.99	14.00
Subordinated	21	0.01	0.33	14.73	296.49	-0.99	7.00
Junior Subordinated	41	0.00	0.22	19.76	597.50	-0.99	7.00
Unknown	23	-0.00	0.11	-0.51	37.28	-0.83	1.00
Oil&Gas	4	-0.01	0.09	-1.55	16.88	-0.55	0.39
Basic Material	23	-0.00	0.22	9.35	208.71	-1.00	5.00
Industrials	30	-0.00	0.18	2.36	45.37	-0.98	2.33
Consumer Goods	35	-0.01	0.32	26.11	937.63	-0.98	11.50
Health Care	16	0.04	0.85	26.89	761.58	-1.00	24.00
Consumer Services	65	-0.00	0.12	0.44	18.25	-0.85	1.00
Telecommunications	42	-0.02	0.20	1.62	39.79	-1.00	3.00
Utilities	46	0.00	0.23	23.76	735.99	-0.99	7.00
Financial	4	0.05	1.06	11.64	147.34	-0.96	14.00
Technology	14	0.01	0.63	20.04	467.84	-0.94	15.00

This table presents returns from a sample of 279 defaulted corporate bonds. The bonds are collected from Thomson/Datastream. The return for each bond-month is the clean price return ($\frac{P_t - P_{t-1}}{P_{t-1}}$). The seniority of the bonds have been identified from the EDGAR database. Bonds where the seniority has been unclear are classified as Unknown. The classification into industries follow the ICB standard.

There is a large negative return in each bond return series (the default) and this influences all moments of the return series. The mean return for the entire sample is negative, but some groups have positive mean returns. The standard deviations are high compared to the mean returns, the skewness is positive and the kurtosis is high. Comparing the sample characteristics for all the defaulted bonds to a random sample of corporate bonds, for instance from Table 2.1 in the first paper in this study, reveals that these bonds have quite different characteristics.[6] Nine months after default six percent of the defaulted bonds have a clean price higher than their face value. Sixteen percent have a clean price lower than two percent of their face value.

Table 2.2. Bounce back and drop dead bonds after default.

Category/Month	1	2	3	4	5	6	7	8	9
Active bonds	279	279	279	278	277	274	274	274	274
Value > face value	14	15	14	16	16	14	16	17	17
Value < 2 percent face value	47	40	43	41	41	40	43	44	43

This table presents the number of bonds that recover after default and the number of bonds that are valued at less than 2 percent of face value up to nine months after the default event.

[6] For the entire sample in the first paper the mean yearly return (recalculated from simple returns) is -0.02, the standard deviation is 0.06, the skewness is -0.49, and the excess kurtosis is -0.41.

2.4.1 Liquidity measures

The liquidity risk has been shown to be important for the pricing of corporate bonds. There are many ways to operationalize the liquidity measure; three examples are measures of traded volume, market impact of a large transaction, and the size of the difference between the bid and ask spreads. The available data has low frequency (monthly) and contains only prices and traded volumes, so the return and volume based liquidity measures are used. Two share price based factors are tested. The idea with the share price based factors is that they capture general sensitivity of asset prices against systematic liquidity risk. Finally two measures are calculated from a sample of 3,774 U.S. corporate bond price series.

The two share based series are calculated according to Sadka (2006) and Pástor & Stambaugh (2003). Both these series are available from 2001 through 2005. The Pástor and Stambaugh series are based on a volume reversal coefficient. They find that their market wide liquidity factor is priced. To complement the share price based liquidity measures, measures for liquidity risk are calculated from the sample of corporate bond returns.

From the sample of corporate bond price series innovations are calculated in line with what Pástor & Stambaugh (2003) does for the stock market. Monthly data give a limited number of data points. The idea is to calculate the return response to trading volume. The response coefficient for each bond (i) is calculated using the OLS regression,

$$r^e_{i,t+1} = \theta_i + \phi_i r_{i,t} + \gamma_i \text{sign}\left(r^e_{i,t}\right) \cdot v_{i,t} + \epsilon_{i,t}, \tag{2.11}$$

where $sign(\cdot)$ is a function that takes on -1 or 1 depending on the sign of the input, and the variables are defined as:

$r_{i,t}$: the clean price return on bond i in month t

$r^e_{i,t}$: $r_{i,t} - r_{m,t}$, where $r_{m,t}$ is the average clean price return on all the bonds in the sample during month t,

$v_{i,t}$: the nominal traded volume reported in the TRAX system for bond i in month t, and

$\epsilon_{i,t}$: the residual

The γ coefficient is the excess return response to trading volume. The $sign(\cdot)$ function eliminates the difference between positive and negative excess returns, making the coefficient linear in absolute volume. The underlying economic idea is that an increase in trading volume inflates the return in the first time period and when the trading volume decreases in the next time period the returns decrease, i.e. a return reversal. If this idea is correct the $\gamma_{i,t}$ can be expected to be negative on average. High trading volumes should be associated with negative excess returns in the next time period.[7] Only bond month observations where there is trade volume reported in TRAX are included in the regression. Monthly return observations with abnormally high (+10%) and low (-10%) returns are excluded. This gives 1,745 coefficient estimates for the entire period. For each time period the average gamma estimate is calculated,

$$\hat{\gamma}_t = \frac{1}{N}\sum_{i=1}^{N}\hat{\gamma}_{i,t}. \tag{2.12}$$

The average return response coefficient is a measure of how large the average return reversal is in the next time period. Pástor & Stambaugh (2003) have a problem with an upwards trend in their sample of NYSE and AMEX bonds. My shorter sample period does not exhibit this problem, and it does not have significant serial correlation[8], so the innovation is calculated in a similar manner, but exclude the dollar value scaling quota,

$$\Delta\hat{\gamma}_t = a + b\Delta\hat{\gamma}_{t-1} + c\hat{\gamma}_{t-1} + u_t \tag{2.13}$$

The regression in equation (2.13) produces serially uncorrelated residuals. The residuals are the part of the changes in return response coefficients that does not depend on earlier changes or levels of return response coefficients. The idea is to clean the return response innovations from time series dependencies.

I calculate the innovation ($\mathcal{L}_t$) in liquidity from the residuals (u_t),

$$\mathcal{L}_t = \frac{1}{100}\hat{u}_t \tag{2.14}$$

The re-scaling by 100 is done to follow Pástor & Stambaugh (2003), but is not necessary for the bond series, since the traded volumes typically are large in comparison to the returns. The effect of not re-scaling means that the factor values are very small and that there will be some very large beta estimates.

In addition to the share based series and the above bond liquidity measure, a second bond liquidity measure, AILLIQ, is calculated in line with Amihud

[7] This is true, the mean γ for all bonds in the sample is negative -2.0e-009 with a standard deviation of 1.3e-007.

[8] The first order serial correlation is 0.20, slightly below Pástor and Stambaugh's 0.22.

(2002).[9] More precisely, the AILLIQ measure is defined here as

$$AILLIQ_t = 1/N_j \sum_{k=1}^{Nj} \frac{|r_{k,t}|}{v_{k,t}}, \tag{2.15}$$

where N_j is the number of bond observations in month t, $r_{k,t}$ is the clean price net return for bond k during period t, and $v_{k,y}$ is the reported daily average nominal volume in the TRAX system. $AILLIQ_t$ is thus the average quota between absolute clean price return and reported transaction volume. In the first month included (February 2001) there are 72 quotes. This is the smallest number of quotes in the sample and the maximum is 1,011.

The measures for liquidity risk are all based on changes in return in relation to trading volumes. The pair wise correlation between the series is calculated, to see if there are similarities between the different liquidity series.

Table 2.3. Pairwise correlation between liquidity measures.

	AILLIQ	$\hat{\gamma}_t$	$\mathcal{L}_t$	PS Level	PS Innov	Sadka TF	Sadka PV
AILLIQ							
$\hat{\gamma}_t$	-0.07						
	(0.50)						
$\mathcal{L}_t$	-0.10	0.65					
	(0.35)	(0.00)					
PS Level	-0.03	0.05	-0.04				
	(0.80)	(0.70)	(0.74)				
PS Innov	-0.03	-0.05	-0.06	0.75			
	(0.81)	(0.70)	(0.64)	(0.00)			
Sadka TF	-0.13	-0.11	-0.04	-0.02	-0.15		
	(0.34)	(0.40)	(0.79)	(0.90)	(0.24)		
Sadka PV	-0.13	-0.27	-0.09	0.04	0.09	0.25	
	(0.32)	(0.04)	(0.52)	(0.78)	(0.49)	(0.05)	

This table presents the pairwise correlations between the different measures of liquidity. The measures are the AILLIQ measure, as calculated in equation (2.15), the $\hat{\gamma}_t$, as calculated in equation (2.12). The $\mathcal{L}_t$ is the innovations in liquidity in the bond market, as calculated in equation (2.14). The two PS series (Level and Innov) are the level and innovations for the stock market in accordance with Pástor & Stambaugh (2003). The two Sadka series are fixed (TF) and variable (PV) price effects, calculated according to Sadka (2006). In parenthesis below each pairwise correlation is the significance level.

The bond based series (AILLIQ, $\hat{\gamma}_t$, and $\mathcal{L}_t$) have insignificant and mostly negative correlations with the share based series. Only a few of the correlations are significantly different from zero. The liquidity series seems to measure

[9]Both bond series are calculated from February 2001 through 2006. Amihud sums over days when there has been trading, while here only the months when the TRAX system has reported trading volume is used in the cross-sectional calculations. Amihud calculates the absolute mean average daily return and here the absolute monthly return is calculated from clean prices, ignoring the possible effect of the accrued coupon.

different aspects of liquidity since they are different from each other. The implication is that all liquidity measures needs to be used in the later tests.

2.4.2 Institutional setting

A company can enter into default in several ways:

- the company fails to pay interest on the due date,
- the company fail to pay the principal on the due date,
- the company breaches any other covenants or warranties connected to the securities and the failure continues, or
- the company declares itself in bankruptcy, insolvency or reorganization.

Investors can purchase corporate bonds at issue or in the secondary market. On the secondary market corporate bonds are either traded over-the-counter or through an exchange. Only some of the corporate bonds that are traded through an exchange are formally listed.

The New York Stock Exchange (NYSE) has over 60 percent of trading and listings in my corporate bond sample. There is no listing agreement for a debt issuer on NYSE, but the regulations for listed companies state that the issuer must release all relevant information immediately upon determining that the interest or principal will not be paid in full. Bond issues that are not formally listed can be traded at NYSE.

Most of the bonds in the sample (at least 233 out of 279) have equities listed on one of the U.S. exchanges. The companies that have listed these bonds are thus required to follow standard disclosure and reporting regulations.

Firms in financial distress have a number of options for how to avoid bankruptcy. The two main options are to do an informal restructuring with the creditors or to file for bankruptcy protection under Chapter 11 of the U.S. bankruptcy code. Asquith et al. (1994) finds that only 42 of their 102 financially distressed firms file for bankruptcy. The firms try to avoid going into Chapter 11 since the process is costly. The way firms handle their distress situation is important for the value of the defaulted bonds.

Even if investors' claims on principal or interest are equivalent from an economic perspective, they might be treated differently in the prescription clauses of the bonds. There are instances of different prescription times for principal and interest. In addition to smaller differences in contractual treatment, Asquith et al. (1994) find that banks almost never forgive principal as part of any comprehensive debt restructuring that include subordinated public creditors.

2.5 Results

2.5.1 Cross-section

The cross-sectional dissemination of the data is done to allow for comparisons between this data set and the data of other studies, for instance by Altman & Kishore (1996) and the yearly Moody's report. Moody's has a larger sample since they include bonds from several countries. The figures include only US corporate bonds, so the parameters differ somewhat from Moody's. In Table 2.4 through 2.6 the recovery rate based on market value grouped by seniority and industry is calculated.

Table 2.4. Average market value recovery rate on defaulted corporate bonds per year by seniority.

	Senior Sec.		Senior Unsec.		Senior Subo.		Subordinated		Junior Sub.		Unknown	
Year	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number
2001	0.80	5	0.51	10	0.48	3	0.34	2	0.21	10	0.81	8
2002	0.85	9	0.49	68	0.41	21	0.43	9	0.58	10	0.59	8
2003	0.43	10	0.35	8	0.28	10	0.56	4	0.84	5	0.77	4
2004	0.98	1	0.55	5	0.52	9	-	0	-	0	-	0
2005	0.83	2	0.61	18	0.56	6	0.68	5	0.73	13	0.69	3
2006	0.94	2	0.71	4	0.46	3	0.75	1	0.79	3	-	0
Average	0.71	29	0.51	113	0.43	52	0.52	21	0.59	41	0.71	23
Book rate	0.62	29	0.31	113	0.27	52	0.25	21	0.46	41	0.64	23
Median	0.89		0.53		0.42		0.53		0.66		0.87	
Std Dev	0.33		0.27		0.30		0.20		0.29		0.27	

This table presents the average recovery rate for defaulted bonds. The recovery rate is calculated from clean prices as $1 + \frac{P_t - P_{t-1}}{P_{t-1}}$. The R^2 and $\bar{R}^2$ for the entire sample are 9.7 and 8.1 per cent respectively. The book rate is the average clean price on the month after default divided by the par value. Each estimate is followed by the number of observations used to calculate it.

The seniority of a corporate bond is an indicator for the level of the recovery rate. There is a pattern where both the average market and the book recovery rate are higher for the senior bonds and the junior subordinated bonds. There is a smile pattern in the average recovery rate. The estimates where calculated using equation (2.7), and the explained variation (R^2) is 9.7 percent for the entire sample. If regressions are run for each individual year, the R^2 is about 80-90 percent. This difference in explained variation indicates that the time variation in recovery rates is high.

The recovery rates of face value are lower than the recovery rates of market value. There are two reasons for this. First, the recovery rate of face value incorporates all price adjustments before the default and the recovery rate of market value only what is lost during the month of default. Second, the recovery rate of market value is calculated with a smaller denominator, due to the partial adjustment in price. The lower recovery rate of face value indicates that the market has anticipated the defaults to some extent.

I divide the sample into the ten ICB sector code industries and present the average recovery rate of market value in Table 2.5.

Table 2.5. Average market value recovery rate on defaulted corporate bonds per year by industry.

	Oil&Gas		Basic Material		Indust.		Consumer Goods		Health care		Consumer services		Telecom		Utilities		Financial		Tech.	
Year	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr
2001	-	0	0.41	4	0.65	3	0.20	2	-	0	0.78	8	0.37	4	0.48	15	0.78	1	0.17	1
2002	-	0	0.51	4	0.50	16	0.63	6	0.55	9	0.60	24	0.38	36	0.64	20	0.19	3	0.48	7
2003	0.68	2	0.48	12	0.24	5	0.41	4	0.29	3	0.69	12	0.05	2	-	0	-	0	0.20	1
2004	0.87	2	0.28	2	0.47	2	0.45	5	0.04	1	0.98	2	-	0	0.98	1	-	0	-	0
2005	-	0	0.80	1	0.82	2	0.58	10	0.88	3	0.68	18	-	0	0.72	9	-	0	0.34	4
2006	-	0	-	0	0.61	2	0.64	8	-	0	0.93	1	-	0	0.95	1	-	0	0.95	1
Average	0.77	4	0.47	23	0.50	30	0.54	35	0.53	16	0.68	65	0.36	42	0.62	46	0.34	4	0.43	14
Median	0.83		0.55		0.59		0.62		0.56		0.66		0.28		0.74		0.27		0.39	
Std Dev	0.23		0.28		0.32		0.32		0.29		0.21		0.24		0.31		0.32		0.30	

This table presents the average recovery rate for defaulted corporate bonds. The recovery rate is calculated from clean prices as $1 + \frac{P_t - P_{t-1}}{P_{t-1}}$. The R^2 and $\bar{R}^2$ for the entire sample are 14.6 and 11.7 per cent respectively. Each estimate is followed by the number of observations used to calculate it.

The results from the industry based sample are similar to the results from the seniority sample, with low panel R^2 and high yearly R^2. Each year in general has only a few data points, so it is not possible to draw any conclusions on the distribution or time variation from this grouping.

Firms in different industries typically have different compositions of assets. The recovery rates grouped by seniority and industry are presented in Table 2.6.

Table 2.6. Average market recovery rate on defaulted corporate bonds by seniority and industry.

	Senior Sec.		Senior Unsec.		Senior Subo.		Subordinated		Junior Sub.		Unknown	
Industry	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr	Rate	Nr
Oil&Gas	0.90	1	0.73	3	-	0	-	0	-	0	-	0
Basic Material	0.41	7	0.60	3	0.46	7	0.59	2	0.48	2	0.39	2
Industrials	0.63	3	0.64	11	0.37	15	-	0	-	0	0.62	1
Consumer Goods	0.49	1	0.51	11	0.37	13	0.75	1	0.79	8	0.98	1
Health care	-	0	0.51	11	0.58	4	0.65	1	-	0	-	0
Consumer services	0.69	6	0.58	17	0.61	6	0.61	10	0.75	13	0.81	13
Telecomm.	0.91	1	0.34	28	0.81	1	0.42	5	0.30	6	0.27	1
Utilities	0.92	9	0.61	19	0.29	1	0.01	1	0.43	12	0.74	4
Financial	-	0	0.58	2	0.04	1	0.17	1	-	0	-	0
Technology	0.95	1	0.42	8	0.38	4	-	0	-	0	0.17	1

This table presents the average recovery rate for defaulted bonds. The recovery rate is calculated from clean prices as $1 + \frac{P_t - P_{t-1}}{P_{t-1}}$. The R^2 and $\bar{R}^2$ are 82 and 23 per cent respectively.

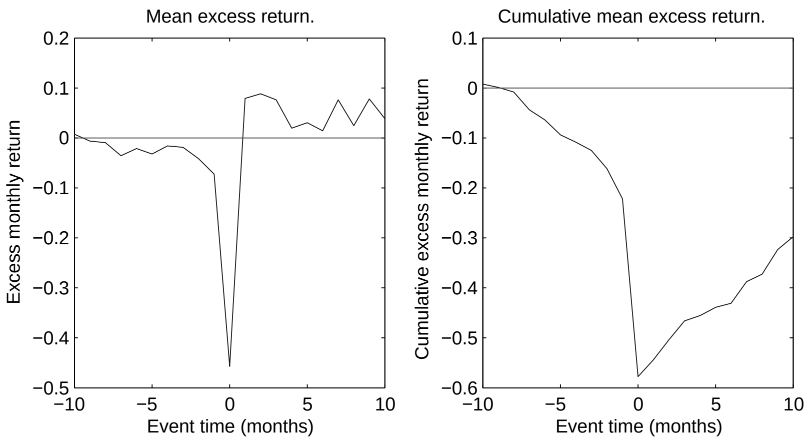
The R^2 is naturally high since there are many explanatory variables to data points. When this is adjusted for in the $\bar{R}^2$ the explanatory value drop considerably. There are even fewer data points per grouping.

The cross-sectional recovery rates are in line with earlier results. There is some time variation, as can be seen in Table 2.4. A different type of time variation is the theme of the next section, the after default time variation.

2.5.2 Time-series

Time-series of defaulted bond returns are problematic, since they contain stale prices and 'dead cat bounce'.[10] Stale prices will in this setup give zero returns on the bond and make it harder to find excess returns. In later periods when the potentially stale price adjusts, it is easier to find excess returns. Cross-sectional smoothing should alleviate this problem. For a schematic overview of what happened to the mean returns of defaulted corporate bonds I include Figure 2.1. The mean excess return in Figure 1 is calculated as $R_\tau = \frac{1}{N}\sum_{i=1 \dots N}(R_{\tau,i} - R^f_\tau))$, where N is the number of bonds, τ is the time period, $R_{\tau,i}$ return on bond i, and R^f_τ the risk free rate. The cumulative mean excess return is the cumulative sum of the presented mean excess returns.

Figure 2.1 Mean excess return on defaulted corporate bonds 2001-2006.



The mean excess return from corporate bonds is negative before the default occurs, implying that investors adjust their pricing before the default. This adjustment can also have happened for many bonds not entering into the default state, so it does not necessarily carry any information. More interesting is that, as can be seen in Figure 2.1, the mean excess return is consistently

[10] A dead cat bounce is when a moderate rise in the price of a stock follows a spectacular fall, with the connotation that the rise does not indicate improving circumstances.

positive after the default. Excess returns have traditionally been attributed to either mispricing or risk. The mispricing argument is that if an asset is underpriced, then the asset will have a higher visible return than is called for by its risk. The risk argument is that the reason there is a high return is that there is compensation for an unknown risk. The fairly sharp rise in returns in the months after the default implies that there might be an overshooting effect, at least for the mean excess return.

The positive mean excess return after default raises the question of what bonds perform well after the default. Is it the same bonds that consistently do well in a turnaround situation? To answer this question I rank the sample into deciles depending on their return one month after the default.

Table 2.7. Average excess return in decile portfolios after default.

Portfolio/Month	1	2	3	4	5	6	7	8	9	10	Mean	ρ
Portfolio 1	-0.38	0.94	0.07	-0.24	0.11	-0.14	0.16	-0.01	0.05	0.16	0.07	-0.39
Portfolio 2	-0.15	0.02	0.06	0.18	0.09	-0.02	0.02	0.02	0.07	0.09	0.04	0.20
Portfolio 3	-0.07	-0.04	0.01	0.10	0.02	0.04	0.04	0.09	0.01	0.02	0.02	0.28
Portfolio 4	-0.02	0.01	0.05	0.06	0.06	0.04	-0.01	0.03	0.03	0.00	0.02	0.33
Portfolio 5	-0.00	0.03	0.52	0.06	0.06	0.01	0.02	-0.01	0.57	0.03	0.13	-0.27
Portfolio 6	-0.00	-0.05	-0.02	-0.05	0.00	0.00	0.42	0.00	-0.02	0.01	0.03	-0.03
Portfolio 7	0.02	0.02	0.00	-0.00	-0.02	0.05	0.02	0.00	0.01	0.02	0.01	-0.15
Portfolio 8	0.06	-0.02	0.02	0.01	-0.00	0.04	0.02	-0.01	0.02	0.04	0.02	-0.36
Portfolio 9	0.18	-0.04	0.04	0.02	-0.01	0.10	0.02	0.06	0.06	0.02	0.05	-0.43
Portfolio 10	1.15	0.01	-0.01	0.00	0.01	0.00	0.05	0.07	0.01	0.02	0.13	-0.02
Mean	0.08	0.09	0.07	0.01	0.03	0.01	0.08	0.02	0.08	0.04	0.05	-0.04

This table presents the average clean price excess return for decile portfolios ranked on log excess return the month after default. The average log excess return for each decile portfolio is presented for ten months following the default. ρ is the first order autocorrelation coefficient for the mean excess returns in each portfolio.

From the mean excess returns per portfolio in Table 2.7 it is not evident that some bonds will recover more than others, or that there is any pattern from the return ranking. Longer ranking periods have been tested, but the results are similar with no clear pattern. The median variability for the portfolio returns is 0.04, with three outliers (Portfolios 1, 5, and 6). The potential turn around in excess returns after default is present in all ten portfolios. The strong excess return could be explained by risk. The correlations are fairly large, but not significant.

Risk explanations

Two risks for corporate bonds can be expected to survive a default; the market and the liquidity risks. The market risk could even be expected to increase since the bond after default has a pay-off profile more resembling a share. Predicting how the liquidity risk should change is not as clear cut. The increase in volume after default decreases the risk associated with selling the bonds, but trading on asymmetric information could increase the risk.

The initial test on the entire sample of defaulted corporate bonds is presented in Table 2.8 below. I test for excess returns before and after the default event. All the liquidity factors calculated in section 2.4.1 are used, but only four of them are presented in Table 2.8. The excluded ones are not significant and the intercept and market beta are no different than the ones presented in Table 2.8. The risk factors of Fama & French (1993) are also used as additional controls, and reported in Table 2.A.1 in Appendix 2.A. The results are similar to the ones in Table 2.8, where the SMB and HML coefficients are significant before default but only HML after. The intercept and market beta are only marginally different when the SMB and HML factors are included.

Table 2.8. Return beta representation for the one-factor model and the liquidity factor.

Panel A. Bond betas before default.															
Intercept	-0.02	-8.13	***	-0.03	-6.21	***	-0.03	-8.31	***	-0.02	-8.00	***	-0.03	-7.83	***
β_{Market}	0.29	4.36	***	0.28	4.22	***	0.26	3.79	***	0.25	3.78	***	0.30	4.56	***
β_{AILLIQ}				2133.11	0.68										
$\beta_{P\&SBond}$							-894640.18	-1.54							
$\beta_{P\&SStock}$										0.18	2.51	**			
β_{Sadka}													1.78	2.13	*
Obs.	2387			2387			2349			2330			2330		
R^2	0.01			0.01			0.01			0.01			0.01		
$\bar{R}^2$	0.01			0.01			0.01			0.01			0.01		
Panel B. Bond betas after default.															
Intercept	0.05	4.08	***	0.06	4.03	***	0.05	4.05	***	0.05	3.98	***	0.05	3.64	***
β_{Market}	0.49	4.42	***	0.46	3.99	***	0.49	4.41	***	0.53	4.53	***	0.52	4.14	***
β_{AILLIQ}				-10379.89	-1.60										
$\beta_{P\&SBond}$							1810131.86	0.74							
$\beta_{P\&SStock}$										-0.06	-0.34				
β_{Sadka}													0.04	0.02	
Obs.	2707			2707			2707			2395			2395		
R^2	0.00			0.00			0.00			0.00			0.00		
$\bar{R}^2$	0.00			0.00			0.00			0.00			0.00		

$r^e = \alpha + \beta F + \varepsilon$

In this table the one-factor model, and two-factor liquidity models, are tested on a sample of defaulted bonds, measured in default time. Panel A consists of the estimated coefficients before the default event and Panel B consists of the estimated coefficients after the default. The data is pooled for ten months before default (Panel A) and ten months after default (Panel B). The market beta (β_{Market}) uses the market factor of Fama & French (1992). The liquidity measures are based on Amihud (2002), Pástor & Stambaugh (2003) and Sadka (2006). The specifications of the liquidity measures are described in Section 2.4.1, equations (2.14) and (2.15). The t-statistics are calculated using robust standard errors. ***, **, and * denotes significance on the 1, 2.5, and 5 percent level.

Two of the liquidity risk factors are significant before the default event. None of the liquidity factors are significant after default. Either the measures of liquidity risk do not influence pricing for bond in default, or the measures are inadequate for capturing the liquidity risk. The AILLIQ and P&S Bond betas are very large, as anticipated.[11] However, they do not seem to influence the size of the intercept much and are insignificant, so the potential problem with bias in the intercept is most likely minor.

The intercept in Panel A is negative, indicating that bonds have poor returns before a possible default. The estimated betas are high for corporate bonds (0.25-0.30) compared to betas for going concerns estimated by Weinstein (1981) (mean betas against stock market 0.03-0.21 during 1964-1972) or the previous chapter in this thesis (0.06 during 2001-2005). Now, these bonds are part of a choice based sample, and do default but this pattern could be present in other bonds as well, so it is not a certain indicator of imminent default. The risk measures in the test do not do a good job at capturing the variability, as measured by the R^2 (1 percent). The intercepts and the market betas are all significantly different from zero, but the liquidity coefficients are not. The low significance of the liquidity coefficients is puzzling, considering that liquidity tends to increase before and after default, and that liquidity risk is a common explanation for corporate bond returns. The liquidity factors have only slightly higher significance if the market beta is left out of the regressions. Hence it is not the market beta that crowds out the liquidity factors.

After the default event, in Panel B, the sample can be considered to be a random selection of defaulted bonds. The intercepts turn positive (0.05-0.06) and are significant. Considering that the intercepts are the average monthly unexplained excess return, they are very high. The median unexplained excess return is about 1.6 percent per month. This difference between mean and median indicates that the distribution is non-normal. The robust standard errors of White (1980) are used to decrease the problem of non-normality. The market beta increases to 0.46-0.53, as could be expected from the bond becoming more equity-like. The variance in the clean price returns increases from a mean of 0.03 before default to a mean of 0.43 after default, more than ten fold. As could be expected from the significant intercept and insignificant parameter estimates the R^2 is zero.

The weak performance of the tested risk factors and the large positive intercept from Table 2.8 indicates that a portfolio of defaulted bonds acquired at default generates excess returns. The spread of returns in Table 2.7 is fairly even, and it looks like most defaulted bonds have an expected positive return. The tentative conclusion is that the average bond is underpriced in the default month, and that at least the risks I have tested are not the reason for this under pricing.

[11] This is a result from the choice not to re-scale the liquidity measures.

Market risk, but not liquidity risk, seems to be important for the pricing of defaulted bonds. The large variation in post default returns and earlier cross-sectional results on industries and seniority give cause to investigate if the risk profile differs in these dimensions.

Seniority

The priority in bankruptcy determines how much is recovered in a bankruptcy. The different priority bonds typically get paid in different fractions, see Table 2.4. The standard deviation also differs between the different priorities. It could thus be expected that both the intercept and the market beta varies depending on priority ranking. The data on the priority ranked portfolios is presented below in Table 2.9.

Table 2.9. Return beta representation for seniority ranked portfolios.

Priority	Intercept			β_{Market}			Obs.	R^2	$\bar{R}^2$
Panel A. Bond betas before default.									
Senior Secured	-0.01	-0.73		0.10	0.63		249	0.00	0.00
Senior Unsecured	-0.03	-6.07	***	0.38	3.93	***	1019	0.01	0.01
Senior Subordinated	-0.03	-3.71	***	0.33	2.14	**	469	0.01	0.01
Subordinated	-0.04	-2.60	***	0.19	0.65		163	0.00	0.00
Junior Subordinated	-0.03	-5.36	***	0.28	2.18	**	322	0.01	0.01
Unknown	0.00	0.09		0.21	1.02		165	0.01	0.00
Panel B. Bond betas after default.									
Senior Secured	0.02	2.39	***	0.10	0.65		286	0.00	0.00
Senior Unsecured	0.05	2.10	**	0.51	1.09		1083	0.00	0.00
Senior Subordinated	0.09	2.28	**	-0.37	-0.39		496	0.00	0.00
Subordinated	0.10	2.20	**	1.77	1.76	*	210	0.01	0.01
Junior Subordinated	0.05	2.10	**	1.01	1.93	*	410	0.01	0.01
Unknown	0.01	1.58		0.41	2.24	**	222	0.02	0.02

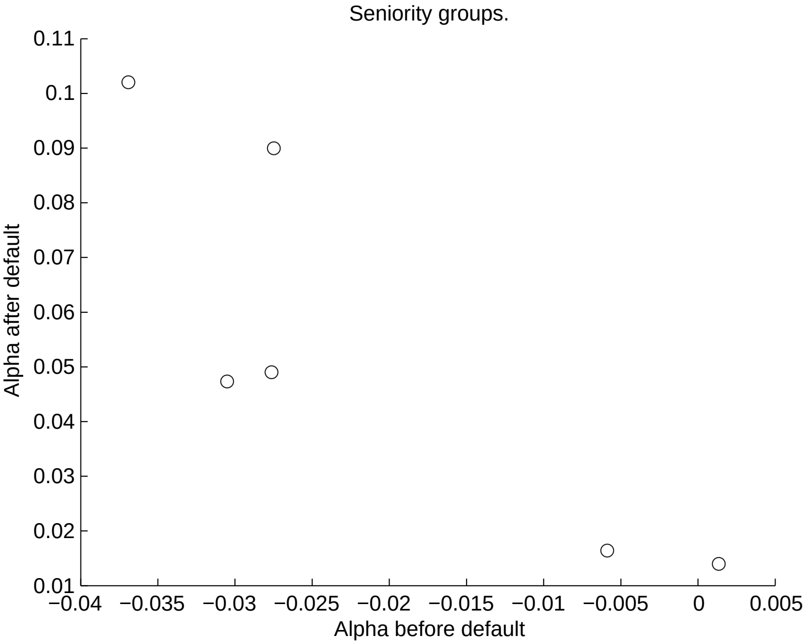
$r^e = \alpha + \beta F + \varepsilon$

In this table the one-factor model is tested on a sample of defaulted bonds, measured in default time. Panel A consists of the estimated coefficients before the default event and Panel B consists of the estimated coefficients after the default. The data is pooled for ten months before default (Panel A) and ten months after default (Panel B). The market beta (β_{Market}) uses the market factor of Fama & French (1992). The t-statistics are calculated using robust standard errors. ***, **, and * denotes significance on the 1, 2.5, and 5 percent level.

The tests for the priority ranked sample in Table 2.9 have similar results as the entire sample in Table 2.8. The exception is that the market beta only is significant for a few of the priority groups before default. The intercept seems to increase with lower priority, indicating that the more insecure bonds are more mispriced at default. The explained variation (R^2 and $\bar{R}^2$) is still low, indicating that the risk, as measured by the tested factors, has little to do with the returns post default. I have tested the Fama & French (1993) factors and they are not significant after default, confirming the general results in Table 2.8.

The intercepts for the seniority groups are negatively correlated before and after default. This is shown for the seniority grouped sample in Figure 2 below. The negative correlation before and after default is valid for the entire

Figure 2.2 Intercepts before and after default for seniority grouped sample.



sample, and to a lesser degree for the industry and return ranked groups. The individual bond before default alphas regressed on corresponding after default alphas give a negative coefficient of -0.6. The alphas after default are on average positive, so either the negative correlation is a sign of an over-shooting effect (mispricing) or there are unknown risks that are not controlled for. To the extent that the risks in Table 2.8 and Table 2.A.1 are controlled for the intercept is still significant and positive. If the explanation is mispricing, then the size of the over-shooting is different for different seniorities. The senior subordinated bonds has a low after default alpha, and less certain categories have larger after default alphas. An economic interpretation of this correlation is that junior bonds are hurt more than senior bonds by the uncertain prospects before default. After default the junior bonds benefit more from resolution of uncertainty.

Industry

The sample is divided into industry portfolios and test for market risk in Table 2.10 below. The idea is that the assets and leverages are similar within industries but differ between industries. The industry sample should help to give an indication if there are specific industry risks that generate the results in Table 2.8.

Table 2.10. Return beta representation for industry ranked portfolios.

Priority	Intercept			β_{Market}			Obs.	R^2	$\bar{R}^2$
Panel A. Bond betas before default.									
Oil&Gas	-0.01	-0.91		0.08	0.21		25	0.00	0.00
Basic Material	-0.02	-1.74	*	0.23	1.03		207	0.01	0.00
Industrials	-0.02	-1.71	*	0.14	0.72		266	0.00	0.00
Consumer Goods	-0.01	-1.70	*	-0.03	-0.15		301	0.00	0.00
Health Care	-0.01	-0.53		0.37	1.82	*	143	0.02	0.02
Consumer Services	-0.02	-4.11	***	0.44	4.15	***	549	0.03	0.03
Telecommunications	-0.04	-4.58	***	0.58	3.16	***	385	0.03	0.02
Utilities	-0.02	-4.57	***	0.12	1.26		358	0.00	0.00
Financial	-0.08	-2.16	**	-1.25	-2.04	**	26	0.14	0.10
Technology	-0.06	-3.30	***	0.26	0.67		127	0.00	0.00
Panel B. Bond betas after default.									
Oil&Gas	0.02	1.68	*	0.76	1.37		40	0.04	0.02
Basic Material	0.06	2.33	***	0.55	0.84		230	0.00	0.00
Industrials	0.04	2.68	***	-0.13	-0.41		285	0.00	0.00
Consumer Goods	0.04	1.02		-0.12	-0.10		311	0.00	0.00
Health Care	0.21	1.33		1.98	0.64		154	0.00	0.00
Consumer Services	0.02	3.81	***	0.76	5.76	***	650	0.05	0.05
Telecommunications	0.02	1.23		0.93	4.21	***	412	0.04	0.04
Utilities	0.05	2.11	**	0.17	0.38		456	0.00	0.00
Financial	0.48	1.29		-5.09	-0.66		40	0.01	0.00
Technology	0.08	2.28	**	0.17	0.24		129	0.00	0.00

$r^e = \alpha + \beta F + \varepsilon$

In this table the one-factor model is tested on a sample of defaulted bonds, measured in default time. Panel A consists of the estimated coefficients before the default event and Panel B consists of the estimated coefficients after the default. The data is pooled for ten months before default (Panel A) and ten months after default (Panel B). The market beta (β_{Market}) uses the market factor of Fama & French (1992). The t-statistics are calculated using robust standard errors. ***, **, and * denotes significance on the 1, 2.5, and 5 percent level.

The pattern for intercepts and betas are similar to Table 2.8 and Table 2.9. However, the industry segmentation singles out two industries where the market risk is important also after default (consumer services and telecommunications). In an unreported test, the SMB and HML are significant at the 1 percent level for the consumer services, and the SMB is significant on the 2.8 percent level for the telecommunications industry. The other industries show the same pattern as found earlier with limited explanatory value for the risk factors tested. The explanatory values are low, but slightly higher for the industries with higher market betas. The negative $\bar{R}^2$s indicate that the models are not adequate descriptions of the data generating process.

Return ranked portfolios

As an additional robustness test, I look at the return ranked portfolios from Table 2.7 and their exposure to market risk. The default and ranking months are not included in the tests. The test against the market factor is presented in Table 2.11.

Table 2.11. Return beta representation for return ranked portfolios.

Priority	Intercept			β_{Market}			Obs.	R^2	$\bar{R}^2$
Panel A. Bond betas before default.									
Portfolio 1	-0.03	-3.02	***	0.61	2.50	***	262	0.02	0.02
Portfolio 2	-0.04	-4.97	***	0.10	0.63		249	0.00	0.00
Portfolio 3	-0.01	-1.61		0.08	0.60		244	0.00	0.00
Portfolio 4	-0.01	-0.82		0.32	2.06	**	246	0.02	0.01
Portfolio 5	-0.03	-2.08	**	0.35	1.19		213	0.01	0.00
Portfolio 6	-0.03	-2.51	***	0.19	0.89		274	0.00	0.00
Portfolio 7	-0.01	-2.11	**	0.11	0.71		180	0.00	0.00
Portfolio 8	-0.02	-3.27	***	-0.04	-0.35		196	0.00	0.00
Portfolio 9	-0.02	-2.39	***	0.41	2.59	***	261	0.03	0.02
Portfolio 10	-0.05	-4.24	***	0.62	2.75	***	262	0.03	0.02
Panel B. Bond betas after default.									
Portfolio 1	0.13	1.17		0.67	0.31		217	0.00	0.00
Portfolio 2	0.05	4.36	***	0.77	3.06	***	252	0.04	0.03
Portfolio 3	0.03	3.54	***	0.26	1.48		248	0.01	0.00
Portfolio 4	0.02	2.69	***	0.96	4.53	***	244	0.08	0.07
Portfolio 5	0.15	1.96	*	-0.41	-0.27		229	0.00	0.00
Portfolio 6	0.03	0.58		0.03	0.02		241	0.00	0.00
Portfolio 7	0.01	2.36	***	0.11	0.90		242	0.00	0.00
Portfolio 8	0.01	1.98	**	0.21	1.39		252	0.01	0.00
Portfolio 9	0.03	2.92	***	1.04	4.86	***	252	0.09	0.08
Portfolio 10	0.01	0.91		0.77	2.41	***	252	0.02	0.02

$r^e = \alpha + \beta F + \varepsilon$

In this table the one-factor model is tested on a sample of defaulted bonds, measured in default time. Panel A consists of the estimated coefficients before the default event and Panel B consists of the estimated coefficients after the default. The data is pooled for ten months before default (Panel A) and ten months after default (Panel B). The market beta (β_{Market}) uses the market factor of Fama & French (1992). The t-statistics are calculated using robust standard errors. ***, **, and * denotes significance on the 1, 2.5, and 5 percent level.

The results for the intercepts and betas and their significance levels before the default event are similar to the earlier tests (in Tables 2.8,2.9, and 2.10). The intercepts are, like in the other tests, positive and often significant. The positive intercepts indicate that there is no problem with stale prices.

2.5.3 Present value of recovery rates

The excess returns that follow the default event cannot be explained by the tested risk factors (market risk, SMB, HML and seven different liquidity factors). The intercepts are significant and large (in the range of 0.01-0.13) after default. The high returns and the low impact of the tested risk factors indicate that the recovery rate might bee biased (too low) one month after default.

Another way of looking at the excess returns post default is to discount the future recovery rates to the default date. If the present values deviate from the recovery rate at default there is a bias. The question is how large the bias is, and if it is economically significant. For this purpose, the recovery rate of market value in column [1], the recovery rate of face value [3] and the present value of the recovery rates of face value [4]-[11] are calculated during nine months after default in Table 2.12. The average market beta is used to calculate discount rate. The market beta increases from 0.24 to 0.63 between the first and second half of the sample. This change in market beta means that the earlier discounted recovery rates are discounted using a too low discount rate, but that later periods have a correct discount rate.

Table 2.12. Risk adjusted discounted recovery rates.

Asset/Recovery rate	Market	Book										
		τ	+1	+2	+3	+4	+5	+6	+7	+8	+9	Obs
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Entire Sample	0.53	0.60	0.40	0.40	0.40	0.41	0.42	0.43	0.43	0.43	0.44	176
Senior Secured	0.59	0.74	0.61	0.62	0.64	0.64	0.64	0.64	0.65	0.66	0.67	17
Senior Unsecured	0.57	0.52	0.34	0.34	0.33	0.34	0.36	0.38	0.39	0.40	0.40	71
Senior Subordinated	0.46	0.45	0.26	0.26	0.26	0.28	0.30	0.30	0.31	0.31	0.31	33
Subordinated	0.60	0.42	0.19	0.23	0.19	0.20	0.22	0.22	0.26	0.31	0.31	11
Junior Subordinated	0.49	0.75	0.51	0.53	0.56	0.56	0.57	0.58	0.60	0.58	0.61	22
Unknown	0.61	0.79	0.63	0.64	0.64	0.70	0.70	0.75	0.74	0.79	0.85	14
Oil&Gas	0.71	0.47	0.37	0.36	0.35	0.37	0.37	0.35	0.39	0.44	0.46	3
Basic Material	0.38	0.51	0.28	0.28	0.29	0.28	0.30	0.31	0.32	0.31	0.33	15
Industrials	0.59	0.56	0.39	0.39	0.39	0.41	0.42	0.44	0.42	0.44	0.44	18
Consumer Goods	0.67	0.53	0.40	0.42	0.42	0.42	0.45	0.47	0.49	0.49	0.49	21
Health care	0.47	0.65	0.40	0.41	0.41	0.44	0.51	0.51	0.50	0.52	0.52	9
Consumer services	0.60	0.68	0.51	0.49	0.50	0.50	0.49	0.50	0.49	0.51	0.50	40
Telecomm.	0.49	0.39	0.19	0.23	0.19	0.20	0.19	0.19	0.23	0.27	0.26	24
Utilities	0.54	0.82	0.49	0.51	0.53	0.51	0.52	0.50	0.50	0.54	0.58	30
Financial	0.58	0.53	0.38	0.43	0.44	0.46	0.44	0.39	0.43	0.40	0.39	2
Technology	0.43	0.35	0.22	0.21	0.23	0.28	0.36	0.40	0.40	0.37	0.36	9

This table presents the net present value of the future book recovery rates, discounted using a risk adjusted interest rate. $PV(RR_{\tau+n}) = \frac{RR_{\tau+n}}{\prod_{i=\tau}^{\tau+n}(1+r_i^f+\hat{\beta}F_i)}$. RR_τ is the recovery rate at default time τ, R^f the risk free interest rate, n is the number of periods after default, $\hat{\beta}$ is the estimated standardized covariance for the asset, and F is the market return.

The results in Table 2.12 are conclusive in the sense that recovery value increases as the months go by [4]-[11] except for consumer services. For the entire sample the average mean discounted recovery value nine months out [11] is four percentage points higher than the recovery value one month after default [3]. The standard method for calculating the recovery rate that uses one month after default seems to underestimate the recovery value by ten percent. The cross-sectional variation is there, both in terms of seniority and industry, but the result with increasing recovery rate over time is robust. Investors that sell corporate bonds one month after default receive, on average, a lower risk adjusted price for their bonds than investors that wait. This could be expected since it is the same result found in Section 2.5.2.

In addition to the calculations for Table 2.12 I have done in-sample tests using the generalized method of moments method (GMM) from Hansen (1982). When there are solutions to the moment conditions[12] the estimates do not deviate more than a few points from the estimates in Table 2.12. I have applied the efficient weighting matrix. The use of GMM allows for calculations of t-statistics on the discounted present value of the future recovery rates in parallel to the estimates in Table 2.12. The estimates of discounted recovery rates are significantly different from zero. In the entire sample the default recovery rate is 0.38 and the nine month out recovery rate is 0.42. The difference between the default recovery rate and the nine months out present value of the recovery rate has a robust t-statistic of about 0.20 and is not statistically significant.

The return tests in Table 2.8 through Table 2.11 measure the same effect as the test of difference in recovery rates. The reason the former tests have significant results and the latter test not is that they are based on many more observations. For each 'entire sample' estimate of returns there are over two thousand observations (Table 2.8) and for the discounted recovery rate there are only 176 (Table 2.12).

The excess simple return for the entire sample is 0.05 per month. The difference between recovery rates (0.40 against 0.44) is only ten percent over nine months. At first glance the monthly returns and the total difference in recovery rate seems unreconcilable. The reason for this apparent discrepancy is that the probability that an investor will receive the expected return or more is less than 50 percent.[13] Compounding over time means that the expected return is going to be higher than the median return (0.016). I.e. large and

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[12] $g_T\left(\hat{\theta}\right) = \begin{bmatrix} \hat{RR} - \frac{RR_{i,n}}{\prod_{j=1}^{n}(1+R_j^f+\hat{\beta}_i\lambda_j)} \\ \sum_{k=1}^{n} R_{i,k} - R_k^f - \hat{\beta}_i\lambda_k \end{bmatrix}$, where $\hat{RR}$ and $\hat{\beta}$ are the estimated parameters, i the bond, n the number of time periods the recovery rate is discounted, R^f the risk free rate, λ the market risk factor, and $R_{i,k}$ the bond return on bond i in period k.

[13] Kritzman (2000) provides an intuitive explanation for this in chapter four "Why the Expected Return Is Not to Be Expected".

unlikely returns increase the expected return. The specification of CAPM used here is based on simple returns, so this is what is reported. However, I have also tested with continuously compounded returns as a robustness check.[14] The size of the estimated excess return decrease (to 0.01-0.02) and is in most cases still significant. The results from tests using log returns are included in Table 2.A.2 in Appendix 2.A.

2.6 Conclusions

The descriptive data on the cross-section for defaulted bonds aligns with previous findings on how defaulted bonds are priced. The findings in the post-default time-series data are new. The claim on the bias in recovery rate estimations on page 76 is validated by the increases in the average discounted recovery rate. Even if the average increases in most groups, it cannot be statistically validated.

My tests for excess returns in defaulted corporate bond returns give significant excess returns. The risks factors I use to explain the returns do not do a good job, with the exception of the market risk. The other factors I have tested and reported are the HML and SMB, and liquidity based factors. The market factor influences the post default return for some portfolios (as can be seen in Table 2.9-2.11.) The other factors give little help in explaining the returns. Perhaps most interesting is the weak performance of the liquidity factors, since they are important for pricing of corporate bonds in general. The return ranked portfolios are the ones most influenced by the market risk factor post default.

The remaining excess return, when some risk factors are controlled for, is positive and significant in my sample, and in the robustness checks (seniority and industry). The dispersion of the returns increases after default, as can be (indirectly) seen in Table 2.8. I can not find a suitable risk explanation for the positive intercepts, so perhaps investor specialization is the key to understanding the apparent mispricing.

The holder of a defaulted bond cannot regain the loss that was incurred at default, but there is no reason to abstain from the high unexplained returns following default. The high excess returns could potentially spill over to bond prices before default, but it is unlikely since the size of the difference between at default and future discounted recovery rates is small (ten percent).

[14]If returns are log normally distributed, and the investment opportunity set is constant Merton (1973) find that his continuous time analog coincides with the capital market line of the one period CAPM.

2.A Appendix

Table 2.A.1. Return beta representation for the three-factor model and the liquidity factor.

Panel A. Bond betas before default.															
Intercept	-0.03	-8.34	***	-0.04	-6.80	***	-0.03	-8.77	***	-0.03	-8.44	***	-0.03	-8.61	***
β_{Market}	0.29	3.91	***	0.29	3.54	***	0.29	3.51	***	0.28	3.50	***	0.30	3.61	***
β_{SMB}	0.38	9.83	***	0.39	10.62	***	0.33	2.12	*	0.37	7.60	***	0.45	7.02	***
β_{HML}	0.30	2.60	***	0.36	4.89	***	0.37	2.62	***	0.29	5.26	***	0.36	3.69	***
β_{AILLIQ}				5827.99	1.63										
$\beta_{P\&SBond}$							-544945.13	-0.42							
$\beta_{P\&SStock}$										0.08	0.97				
β_{Sadka}													-1.20	-0.93	
Obs.		2387			2387			2349			2330			2330	
R^2		0.02			0.02			0.02			0.02			0.02	
$\bar{R}^2$		0.02			0.02			0.02			0.02			0.02	
Panel B. Bond betas after default.															
Intercept	0.05	3.64	***	0.06	3.36	***	0.05	3.63	***	0.05	3.21	***	0.06	3.63	***
β_{Market}	0.55	4.40	***	0.51	3.60	***	0.51	3.74	***	0.69	4.64	***	0.58	3.96	***
β_{SMB}	0.15	0.95		0.15	1.02		0.31	1.70		0.08	0.44		0.19	0.72	
β_{HML}	0.52	1.51		0.42	3.21	***	0.43	2.92	***	0.83	5.17	***	0.94	3.32	***
β_{AILLIQ}				-8296.83	-1.19										
$\beta_{P\&SBond}$							2405401.33	0.81							
$\beta_{P\&SStock}$										-0.27	-1.30				
β_{Sadka}													-3.96	-1.03	
Obs.		2707			2707			2707			2395			2395	
R^2		0.00			0.00			0.00			0.00			0.00	
$\bar{R}^2$		0.00			0.00			0.00			0.00			0.00	

$r^e_{\tau,i} = \alpha + \beta F_{\tau,i} + \varepsilon_{\tau,i}$

In this table the three-factor model is tested on a sample of defaulted bonds, measured in default time. Panel A consists of the estimated coefficients before the default event and Panel B consists of the estimated coefficients after the default. The data is pooled for ten months before default (Panel A) and ten months after default (Panel B). The market, the SMB and HML betas (β_{Market}, β_{SMB}, β_{HML}) uses the market factor of Fama & French (1992). The liquidity measures are based on Amihud (2002), Pástor & Stambaugh (2003) and Sadka (2006). The specifications of the liquidity measures are described in Section 2.4.1. The t-statistics are calculated using robust standard errors. ***, **, and * denotes significance on the 1, 2.5, and 5 percent level.

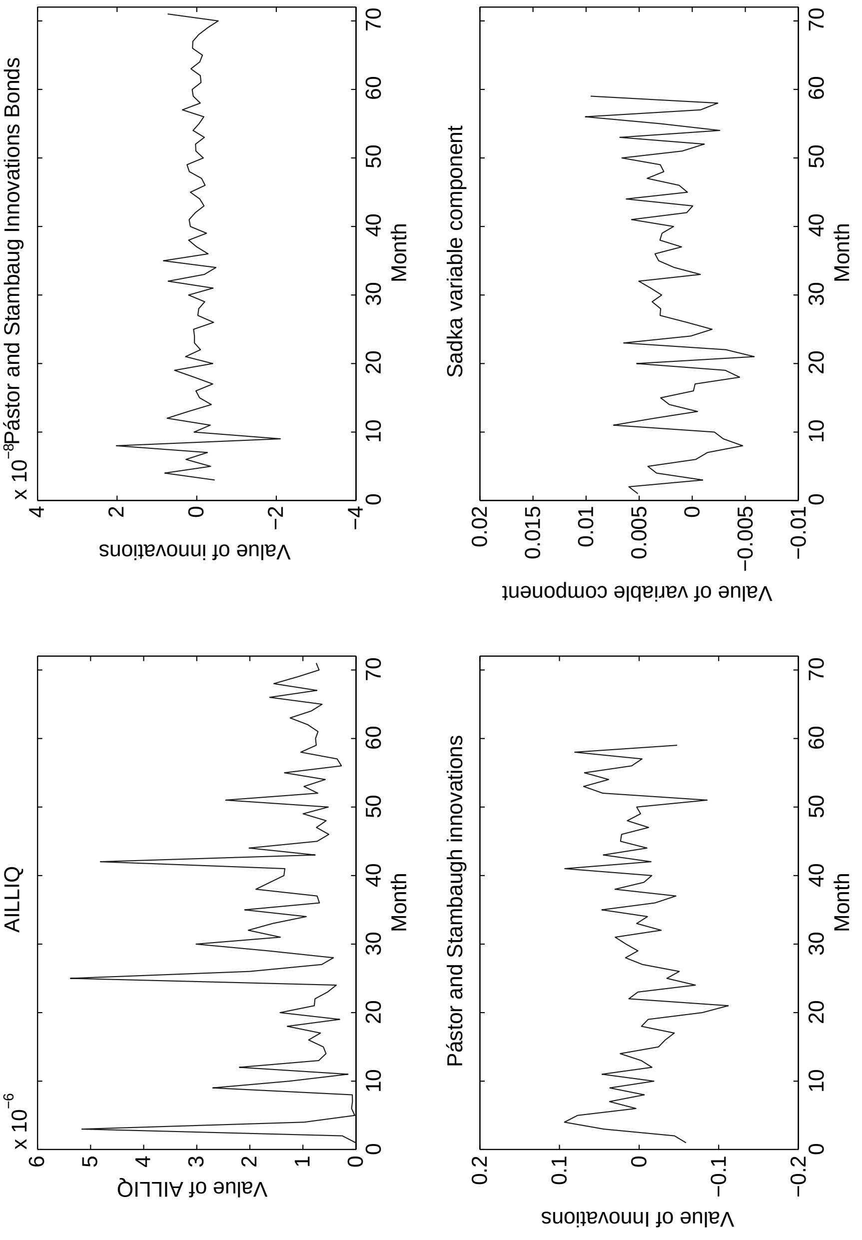
Table 2.A.2. Log Return beta representation for the one-factor model and the liquidity factor.

Panel A. Bond betas before default.															
Intercept	-0.04	-9.82	***	-0.04	-7.30	***	-0.04	-9.98	***	-0.04	-9.68	***	-0.04	-9.16	***
β_{Market}	0.27	2.87	***	0.27	2.79	***	0.26	2.54	***	0.23	2.41	**	0.29	3.04	***
β_{AILLIQ}				1314.22	0.35										
$\beta_{P\&SBond}$							-668626.93	-0.85							
$\beta_{P\&SStock}$										0.21	2.46	**			
β_{Sadka}													3.07	2.69	***
Obs.		2387			2387			2349			2330			2330	
R^2		0.00			0.01			0.01			0.01			0.01	
$\bar{R}^2$		0.00			0.00			0.00			0.01			0.01	
Panel B. Bond betas after default.															
Intercept	0.01	2.51	**	0.02	2.86	***	0.01	2.47	**	0.01	2.64	***	0.01	1.18	
β_{Market}	0.47	5.07	***	0.45	4.88	***	0.47	5.14	***	0.46	4.20	***	0.53	5.75	***
β_{AILLIQ}				-5620.01	-1.75										
$\beta_{P\&SBond}$							-1662747.84	-1.40							
$\beta_{P\&SStock}$										0.16	1.12				
β_{Sadka}													2.93	2.07	*
Obs.		2707			2707			2707			2395			2395	
R^2		0.01			0.01			0.01			0.01			0.01	
$\bar{R}^2$		0.01			0.01			0.01			0.01			0.01	

$r^e = \alpha + \beta F + \varepsilon$

In this table the one-factor model, and two-factor liquidity models, are tested on a sample of defaulted bonds, measured in default time. Panel A consists of the estimated coefficients before the default event and Panel B consists of the estimated coefficients after the default. The data is pooled for ten months before default (Panel A) and ten months after default (Panel B). The market beta (β_{Market}) uses the market factor of Fama & French (1992). The liquidity measures are based on Amihud (2002), Pástor & Stambaugh (2003) and Sadka (2006). The specifications of the liquidity measures are described in Section 2.4.1, equations (2.14) and (2.15). The t-statistics are calculated using robust standard errors. ***, **, and * denotes significance on the 1, 2.5, and 5 percent level.

Figure 2.3 Liquidity measures.



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Chapter 3

Capital Structure Choices

Abstract

I test the trade-off and pecking order theories using both established tests from the literature and new tests. The main contributions of this paper are the new tests of financing of operating net assets (for the pecking order theory), the mean reversion tests (for the trade-off theory) and the test of mean reversion and trends. These tests allow for extended conclusions on the validity of the pecking order versus the trade-off theory.

The trade-off theory is validated in standard tests, as well as in the new tests. I reject the asymmetric information based empirical predictions of the pecking order theory, but not the profitability based empirical predictions. The conclusion from the pecking order tests is that firms' capital structure has more to do with their historical profitability (return on equity) than the solution to an asymmetrical information problem.

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3.1 Introduction

The literature on financial structure suggests two principal models for the capital structure choice; the trade-off and the pecking order theories.[1] In this paper I will first test the trade-off and the pecking order theories on Swedish data. After these tests I will test the trade-off theory against the historical chance aspect of the pecking order theory. The historical chance aspect is the idea that a firm's capital structure merely is explained by its past profitability.

3.1.1 Problem

The main idea in the trade-off theory is that benefits and costs of debt financing yield an optimal debt-to-assets ratio $(D/A)^*$ for a company. For there to be a trade-off result there has to be both positive and negative effects of debt financing. Incurring an increase of debt can enhance the total value of the company in two ways; i) interest payments are tax deductible (dividends are not), and ii) the agency cost of cash flows is lower with debt financing.[2] The value of the company should thus increase as the level of debt increases.[3] The drawback of debt financing becomes apparent when a company increases its level of debt to high levels. The risk of bankruptcy increases as the level of debt increases. The bankruptcy procedure redistributes asset ownership, and this redistribution process is costly.[4] There are numerous other suggestions

[1] A theory on capital structure is a logical structure that describes how firms choose their leverage. A theory is predictive, logical and testable. In contrast a hypothesis is a specific statement on application of the theory that needs evaluation. The mixed evidence on the capital structure theories raises the issue if they should be referred to as theories or merely hypotheses. I align with common practise in the literature and refer to them as theories.

[2] The agency cost of cash flow is incurred when a company, that generates large amounts of cash flows, invests them unwisely. The idea is that the managers do not want to return the cash flows to the owners, but instead invest them in less profitable ventures, decreasing the value of the company. A higher level of debt decreases the cash flows through interest payments and thereby decrease the likelihood of unwise investments.

[3] Miller (1977) finds that there is an equilibrium debt-equity ratio for the corporate sector, but there is no optimum debt ratio for any individual firm. In short the argument is that the price of debt and the price of equity is changed by investors so that in equilibrium there are no gains from adjusting the debt-equity ratio for any individual firm.

[4] The direct costs, such as professional fees, loss of the tax shield, and assets sales at a discount, have been measured by Warner (1977), Altman (1984), and Weiss (1990). The estimates vary between Warner's railroads with 2.8 percent and Altman's 6 percent of total value. Andrade & Kaplan (1998) study the indirect costs of bankruptcy. The estimates of indirect costs, such as lost growth options or future business opportunities, less firm specific investment, and waste of management resources, are very uncertain and typically estimated to be a bit higher than the direct costs at about 10-20 percent of firm value before bankruptcy.

on the benefits and drawbacks of debt financing, but they are all variations of the trade-off theme.

Donaldson (1961) introduced a framework consistent with the pecking order theory, that Myers (1984) revived and named. In this theory it is assumed that there are two types of companies, 'good' and 'bad'. Both types want to raise capital, and the *first best* would be that both firms issue securities at fair value. However, since the bad firm would rather have the lower financing cost of the good firm it has incentives to misrepresent itself as a good firm. The market cannot separate the two types and will price security issues at an average fair value. The average fair value implies a low costs of capital for the bad firms and a high cost of capital for the good firms. However, different types of securities are more or less sensitive to the firm being good or bad, i.e. they have different information sensitiveness. A good firm will then use the least information sensitive financing first (internal funds) before it issues any securities. A bad firm has typically little internal funds and is forced to issue securities. The market interprets the choice to issue securities as a signal of the quality of the firm and sets the price of the securities accordingly. This leads to firms choosing the least information sensitive financing first, in a pecking order. The pecking order theory in itself does not really imply anything about firm leverage; it is a theory of how firms acquire new financing. As a theory of finance, there can be other reasons for the existence of a pecking order. I separate the asymmetrical information based and the historical chance base parts of the pecking order. The 'historical chance' idea is based on Myers (1984) idea of firms having sticky dividend policies and unpredictable variations in their profitability.

The historical chance aspect of the pecking order story is closer to the idea of Miller (1977) about "neutral mutation". It is not quite the same, where Miller argues that firms' financing patterns depend on harmless habits, I argue that they depend on historical profitability. The dispersion in leverage for companies is then explained by some companies having been "lucky" and other companies "unlucky". The lucky companies started out in profitable businesses or organized themselves in an efficient way. The natural selection[5] is not strong enough during the normal business cycle to separate the lucky companies from the less fortunate ones. This process gives a universe of companies with different capital structures. Firms with a strong profitability use strategies to safeguard their position; for instance brand building, monopolizing production resources, decreasing risk taking, or investing in research.

[5]Only part of a "natural selection" is applicable; firms that are not competitive go out of business, but of course firms spawn no new firms.

Firms with superior research or better brands are more likely to attract and create growth options. This situation translates into higher profitability for the "lucky" firms over longer periods of time. There is plenty of piecemeal evidence that some firms are steadily more profitable than their competitors, such as Coca-Cola, Goldman Sachs, and Microsoft. The higher profitability carries over into lower leverage through sticky dividend policies.[6] The sticky dividends are documented by Lintner (1956). The empirical consequence of this is that firms which generate much internal funds decrease their leverage and firms that generate less internal funds increase their leverage. Hence, historical predicts trends over time in leverages. The historical chance is a testable part of the pecking order theory. One effect of a historical chance aspect is that capital structures should change slowly over time.

3.1.2 Previous research

When the trade-off theory has been combined with a constraint on available debt, it has done fairly well in theoretical comparisons against the debt capacity hypothesis; see Baron (1975) or Kim (1978) for analyses. In empirical tests against the pecking order theory the support for the trade-off theory has been less strong. Shyam-Sunder & Myers (1999) use simulations to test the statistical power of tests on the pecking order and trade-off theories. They find that the pecking order tests have power to reject the pecking order in time series tests, but that their trade-off tests have a very weak statistical power. Hovakimian et al. (2001) find that even if past returns seem to matter for leverage, firms move towards a trade-off predicted capitalization when issuing or retiring more substantial amounts of capital. Fama & French (2002) find that the empirical predictions shared by the trade-off and the pecking order theory are confirmed. They also find that more profitable firms tend to have lower leverage, a prediction from the pecking order, but not in line with a trade-off theory. Even if it seems like the trade-off does poorly against the pecking order in these tests, Frank & Goyal (2003) find that support for the trade-off theory tends to be increasing over time. Graham & Harvey (2001) find in a survey of 392 CFOs that only 19 percent of the responding firms

[6] Consider a firm in steady state that only relies on internal funds. Assume the firm has the same amount of debt in all time periods and that the amount is above zero ($D_{t...T} > 0$). The only new financing of this firm is net income (X_t) at time t minus dividends (d_t). Define book leverage $L_t = \frac{D_t}{A_t}$, the ratio between debt and assets. If this firm generates more income than it distributes as dividends $X_t - d_t > 0$, the next period leverage is decreasing; $L_{t+1} = \frac{D_{t+1}}{A_{t+1}} = \frac{A_{t+1} - E_{t+1}}{A_{t+1}} = 1 - \frac{E_{t+1}}{A_{t+1}} = 1 - \frac{E_t + X_t - d_t}{A_t + X_t - d_t} < 1 - \frac{E_t}{A_t} = L_t$. The firms that generate and keep internal funds will have a lower leverage in the next period, ceteris paribus. Cf also Johansson (1998), chapters 7 and 9.

claim *not* to have any capital structure target. In this light the poor empirical performance of the trade-off model is a bit surprising.

There has been no explicit test of the historical chance aspect of the pecking order theory before in the capital structure literature. The capital structure literature is substantial however, so there are results that can be interpreted in a historical chance context. Baker & Wurgler (2002) finds that capital structures are persistent over time, in line with the slow change predicted by the historical chance aspect. The evidence favoring the pecking order theory over the trade-off theory tends to favor a historical chance interpretation, but not always. Welch (2004) decomposes capital structure changes into issuing/retiring activities and stock price changes. Welch finds that stock price changes account for 60-70 percent of capital structure changes and that companies tend to issue equity when profits are high but debt when profits are low. According to the pecking order theory there is no specific reason to issue equity when profits are high. Investments should be financed with internal funds or debt (not information sensitive) for profitable companies.

In a study of Swedish industrial companies, Bertmar & Molin (1977) show that companies with a lower book return on total capital tend to have increasing debt-to-equity ratios. Their conclusion is that growth in equity is primarily a function of the return on equity after tax. The companies in their sample have fairly stable dividend policies, so more profitable firms accumulate capital and less profitable firms decrease the proportion of equity financing.

3.1.3 Contribution

I test the trade-off and pecking order theories on Swedish data using new and standard tests from the literature. The standard tests are done to set a benchmark since there are no previous tests of the theories on this sample. In these tests I find strong support for the trade-off theory and weak support for the pecking order theory. There are two different sets of tests for the pecking order theory. The first set is more direct and tests how a deficit is financed (asymmetrical information based). The second set concerns the time-series properties (historical chance), where more profitable firms are hypothesized to have decreasing leverage. My results correspond to earlier studies, in that the time-series results are strong and the direct tests are weak. In the last type of tests I test the trade-off against the historical chance. These tests are joint tests of mean-reversion[7] with trend regressions. From these tests it can be concluded that there is a strong mean reversion (trade-off) and a trend

[7]Note that also the tests when the optimal capital structure changes are referred to as mean-reversion tests.

(historical chance). The pecking order performs well in the time-series tests, but poorly in the direct tests. The conclusion is that there is something else than a pure pecking order that explains firms' financing choices.

The structure of the paper is as follows. In section 3.2 the empirical predictions are developed. In section 3.3 I give a brief outline of the data and develop the predictions into econometric tests. Then in section 3.4 the results from the empirical tests are described and analyzed. In the final section I present and discuss the main findings of the study. All sections are divided into subsections where applicable, for the three main test themes of i) the trade-off theory, ii) the pecking order theory, and iii) historical chance and trade-off.

3.2 Predictions for the capital structure models

The trade-off and pecking order theories have different consequences for firm's choice of capital structure. In this section I describe the predictions that follow from the pecking order and trade-off theories, and how the historical chance differs from the trade-off theory. The specifications of the tests are presented in the econometric section.

3.2.1 The trade-off theory

Claim 3.1 *The capital structure of a firm approaches a level where the market value of the firm is maximized.*

There is an optimal ratio of debt-to-assets $(D/A)^*$ according to the trade-off theory. The optimal ratio can be stable or change from period to period. Firms strive towards this optimal ratio by adjusting dividends, issuing shares, borrowing or issuing bonds. It is costly for companies to change their financial structure. The cost of adjustment make continuous adjustments undesirable and thus the adjustment process is expected to be slow. The optimal ratio is not observable, so it is assumed that firms attain their target capital structure on average. If the adjustment process is not instantaneous, the firms' behavior can be modeled with a mean-reversion process. At each instant the firm closes a part of the gap to the optimal leverage. The distance between the next and the current leverage ratio is a function of how far the firm is from the optimal ratio $\left(\frac{D}{A}\right)^*$;

$$\left(\frac{D}{A}\right)_{t+1} - \left(\frac{D}{A}\right)_t = \gamma \left[\left(\frac{D}{A}\right)_t - \left(\frac{D}{A}\right)^*\right], \tag{3.1}$$

where D is net debt, t is a time subscript, and γ is the speed of adjustment. When the capital structure moves away from the optimal ratio the reversal process can be estimated. If there is a mean reversion process and the ratio deviates from its optimal value, then it is possible to measure the speed of the adjustment in γ. A low or insignificant γ would suggest that the difference between time periods does not relate to a deviation from the optimal level.

The predictions for dividends and capital acquisitions are related to the difference between the current level and the optimal ratio. If the firm has leverage above its optimal value it can be expected to decrease its leverage, and vice versa. Earlier studies have found factors that relate to the optimal leverage ratio. Two factors that supposedly increase leverage are a strong profitability and a high tax rate. Both examples increase the value of the tax shield.[8] A more profitable company has a higher probability of being able to use an interest cost tax shield and a higher tax rate increases the size of the tax shield. Three examples of negative factors are growth options, the volatility of net cash flows, and limits set by creditors. If the company is liquidated the growth options expire worthless. High volatility of cash flows increases the probability of default. Creditors set the price of credits in accordance to expected risk, and a higher leverage is typically associated with a lower rating and a higher cost of borrowing.

A firm that makes investments would want to keep roughly the same capital structure. Either the firm has to raise equity and debt in the correct proportions, or it would have an adaptation process where it reaches the desired level over time. It can thus be assumed that changes in the asset base of a company either have no effect on firm leverage or that changes in the asset base give rise to an adaptation process.

[8] If there is a difference in interest rate income and equity income for investors, there is a positive value associated with incurring debt for a company. Interest payments are typically tax deductible for companies, so if the company income taxation rate and the dividend income taxation rate is less than the interest income tax rate ($(1 - T_{interest}) > (1 - T_{company})(1 - T_{dividend})$) there is a value to incurring debt.

3.2.2 The pecking order theory

Claim 3.2 *Firms are not concerned with capital structure per se, but with costs associated with asymmetric information.*

Two asymmetrical information based tests will be used for testing the pecking order theory.

In the first tests of the pecking order theory the sample is divided into firms with surpluses and firms with deficits in their financing of changes in operating net assets. If the pecking order theory is correct, these firms should retain internal funds in excess of their financing need for their operating net assets. Any expansion in assets should be financed with internal funds. The firms that have a deficit in their financing should fill their excess needs with increases in net debt. These implications from the pecking order theory are tested together with modified versions which includes a sticky dividend policy.

The second test hinges on the idea that firms with investment opportunities, or financial deficits, only use debt if they are out of internal funds. This idea, used by for instance Shyam-Sunder & Myers (1999) and later Frank & Goyal (2003), is to figure out which firms have had large investments. When firms have a financial deficit and need to acquire new outside financing, the choice of financing can reveal if the pecking order holds. The pecking order theory prescribes that most firms would acquire new financing in the form of debt before they issue equity.

Claim 3.3 *The capital structure of firms is decided by their historic profitability.*

The third claim is the historical chance aspect of the pecking order. The historical chance is tested as a competing explanation to the trade-off. In principle this boils down to whether firms make active capital structure choices and change their structure to an optimal level or not.

There are predictions both for the cross-section and the time series dimension of data for the historical chance hypothesis. In the cross-section more profitable firms should have lower debt-to-assets ratios than less profitable firms, i.e. return on equity (ROE) should be negatively correlated with leverage. In the time series, firms with low leverage would tend to get even lower leverage, rather than reverting to a mean over time. For the historical chance there is no reason to believe that there should be any mean reversion. Instead the idea is to see if the dispersion in the sample increases over time, where low leverage firms decrease their leverage and high leverage firms increase their leverage. Finding a dispersion pattern of this kind would support the pecking order theory and the historical chance.

3.3 Data

Ecovision, a company specializing in collecting and selling financial data, has provided the data. The data set has been manually corrected and obvious errors have been eliminated.[9] The data set did not include the market capitalization of firms and this information has been added from Datastream. The market capitalization is calculated using the total number of issued shares for each company times the last traded price at each year end. The price of each class of shares is used for companies with dual class shares.

The data set comprises all industrial companies that have been listed on the main list (A-list) of the Stockholm Stock Exchange (SSE)[10] at any time from 1990 to 2004. Some of the industrial companies have large financial operations, but I have not been able to separate these activities. The sample includes companies which are not domestic, but listed on the SSE. The data consists of accounting measures and the market capitalization of companies as of the last of December each year. Companies are excluded from the sample for different reasons. Firms that have defaulted are included in the sample until they are de-listed. Out of a total of 133 companies in the sample only 30 are listed over the entire period 1990 to 2004.[11] There are 1,325 leverage observations in total, or on average about ten per company. I describe some of the variables in the data set with summary statistics in Table 3.1.

[9] Less than one percent of the original sample was eliminated. Examples of obvious errors are wrong input of balance sheet items, and wrong classification of items in both the balance sheet and the income statement.

[10] The actual name of the exchange is 'Stockholmsbörsen'. Since April 2003 there are two exchanges (Stockholmsbörsen and Nordic Growth Market) in Stockholm.

[11] The robustness of the results have been tested using a sub-sample comprising only the firms listed during the entire sample window. The results support the findings reported from the full data set, even if significance levels are somewhat lower due to the smaller sample.

Table 3.1. Summary Statistics (MSEK)

Variable	Nr obs.	Mean	Median	Std Dev	Skewness	Kurtosis
Equity	1325	9682	1870	21946	4.94	37.59
Debt	1325	16073	3674	32351	3.49	16.98
Assets	1325	26072	6075	52356	3.60	19.70
Long Term Assets	1325	13085	2984	25186	3.31	15.36
Short Term Assets	1325	12979	2378	31026	4.98	40.66
Minority	861	441	37	1235	6.39	55.91
Market Cap	1131	30896	3864	120782	9.70	121.97
Sales	1322	23114	5137	48655	4.97	47.67
R&D Expenses	334	3992	515	9017	3.19	13.12
Depreciation	1273	1080	185	2573	4.80	32.46
Earnings	1318	1231	177	4925	9.14	142.87
EBIT	1298	1870	226	6887	9.66	149.94
Mean EBIT	1028	1910	261	6159	6.89	61.52

The Long Term Assets are assets that the company can be expected to maintain over a long time horizon (goodwill, real estate, machinery and equipment etc). The short term assets are inventory and short term claims on clients etc. The Market Cap is the estimated market capitalization of the firm as of last of December each year. EBIT is earnings before interest net cost and tax. The Mean EBIT is a three year average of EBIT. (Three extreme outliers have been removed from the calculation of the Summary Statistics.)

The data in Table 3.1 is in nominal terms. Some of the companies in the sample do not report in Swedish Kronor (SEK), and these financial reports have been converted into SEK using the last exchange rate each year. Three companies in Table 3.1 (Ericsson, Nokia and Norsk Hydro) are large in comparison to the others. These companies are the main reason for the differences between mean and median values in Table 3.1.

The institutional framework has changed over the fifteen year period 1990-2004. The taxation regime is described in Appendix 3.A, but importantly there has been a tax advantage to incurring debt for firm.[12] Sweden disbanded the policy of a fixed exchange rate in 1992, joined the European Union in 1995, and changed the accounting regulation just to name a few changes. However, there is no specific reason as to why the sample period should not be representative for the Swedish economy; it contains high and low interest rates, booms and busts on the stock market.

The cross-section of firms varies in size and in order to remedy any heteroscedasticity problem the accounting numbers for earnings, costs, etc are scaled. The scaling is done with total assets (A) since it does not present problems with negative or small denominators. In Table 3.2 some common measures of capital structure are presented for the sample.

[12]The requirement $(1 - T_{interest}) > (1 - T_{company})(1 - T_{dividend})$ was filled for Sweden since $T_{interest}$=30 percent, $T_{company}$= 28 percent, and $T_{dividend}$=30 percent. The company tax rate was lowered from 30 percent during the sample period.

Table 3.2. Key ratios

Variable	Nr Obs.	Mean	Median	Std Dev	Skewness	Kurtosis
$\frac{Debt}{Equity_M}$	1131	1.92	1.06	3.86	12.68	242.62
$\frac{Debt}{Equity_B}$	1325	2.21	1.79	2.81	-9.78	312.86
$\frac{Debt}{Assets_M}$	1224	0.55	0.54	0.24	0.11	2.34
$\frac{Debt}{Assets_B}$	1325	0.63	0.64	0.15	0.60	16.87
ROE	1192	0.121	0.117	0.25	-0.91	53.06
ROA	1157	0.088	0.081	0.08	0.95	10.06
COD	1128	0.046	0.037	0.12	28.91	910.82

The subscripts on *Equity* and *Assets* indicate if they are based on market (M) or book (B) value of equity. ROE is return on equity, calculated as earnings after tax at time t divided by total equity at time $t-1$. All return measures are calculated in this fashion. ROA is return on total assets, calculated as operating earnings divided by total assets. Cost of debt (COD) is interest paid divided by total debt. The leverage ratios are the average leverage for all firms at each year end. (Three extreme outliers have been removed from the calculation of the key ratios.)

The subscript on *Equity* and *Assets* indicate whether the value of owners equity is based on market value ($Equity_M$) or book value ($Equity_B$). ROE, ROA, and COD are book returns on equity, total assets and cost of debt, respectively. The return on equity is calculated as earnings after tax in relation to owners equity, the return on total capital is earnings before interest expense and taxes divided by total assets, and the return on debt is the interest expense to total debt. A few distressed firms become highly leveraged and have a large impact on the debt-to-equity measure. Both the debt-to-assets ratio and the return to total assets are similar in size to the results found by Bertmar & Molin (1977).[13] This similarity is surprising since there are 18 years between the two samples. However, this is at least further evidence that the sample period is representative for the general distribution.

A number of different industries are present in the sample. The Industry Classification Benchmark (ICB) is used to classify the companies, and some characteristics for the industries are presented in Table 3.3 below. The sample is dominated by industrial companies, which is representative for the SSE main list.

[13]See for instance Table 13:2 and Table 13:7 on pages 284 and 297.

Table 3.3. Descriptives per Industry (MSEK)

Industry (ICB)	Nr obs.	Book assets	Market equity	ROE	ROA	$\frac{Debt}{Assets_M}$	$\frac{Debt}{Assets_M}$ st. dev	$\frac{Sales}{Assets_M}$
Oil & Gas	12	70985	138467	0.129	0.043	0.56	0.08	0.80
Basic Materials	174	33701	44623	0.136	0.062	0.44	0.17	0.89
Industrials	542	12002	17658	0.097	0.034	0.60	0.23	1.12
Consumer Goods	112	8494	14266	0.141	0.058	0.59	0.20	1.69
Health Care	52	144709	59147	0.230	0.112	0.34	0.26	0.80
Consumer Services	64	3155	8720	0.169	0.046	0.50	0.26	3.24
Telecommunications	7	160185	140833	0.101	0.051	0.32	0.04	0.49
Utilities	35	13458	16483	0.150	0.066	0.44	0.21	0.39
Real Estate	103	3530	6336	0.061	-0.037	0.67	0.24	0.24
Technology	91	149185	65925	0.166	0.063	0.39	0.25	1.38

The subscripts on *Assets* indicate that the ratio is based on market value of equity. ROE is return on equity, calculated as earnings after tax at time t divided by total equity at time $t-1$. All returns measures are calculated in this fashion. ROA is return on total assets calculated as operating earnings divided by total assets. The leverage ratios are calculated as the averages for all firms outstanding at year end.

The reported items do not seem to vary much between different industries.[14] The return to total capital (ROA) only varies by a few percentage points, except for the health care and real estate industries. The debt-to-asset ratio for the industries are within one standard deviation from the average of the total sample (0.55). There is some industry variation and within the industries the variation can be substantial, as seen in the standard deviations in the second to last column.

The development over time of central variables (leverage, returns and average size of listed firms) are described in Appendix 3.A. In short

- the debt-to-asset ratio is decreasing over time,

- the returns are fairly stable around their means except for 1992 when they are very weak, and

- the average size of assets triple from 1990 to 2005.

In Appendix 3.A there is a short description of the tax regime in Sweden during the sample period. The tax regime has been stable from 1992 to 2004 with only minor changes. In short the tax rates have been 30 percent on capital gains, 30-55 percent on marginal personal income, and 28-30 percent on company profits.

[14]The 'Oil & Gas' and 'Telecommunications' industries contain only one company each and thus do not have a major impact on the results. This is fortunate since these sectors are regulated during the period.

3.3.1 Econometric models

The tests for the three claims are specified here. The outline of each subsection is first a short background on earlier tests, followed by the test specification and then a short discussion on the tests.

Testing the trade-off theory

The trade-off theory of Modigliani & Miller (1958) is a theory based on market values. Fama & French (2002) (page 9) claims that the trade-off theory could apply to assets valued at market values as well as book values. I include tests for book leverage in Appendix 3.E for comparability. The market value of equity is available for all firms in the sample, since the companies have listed shares. To the extent possible both the market-value leverage and book leverage[15] are used for the tests.

The choice of debt measure can be important. I have run all tests using two measures of debt, 'total debt' and 'net debt'. The results differ in size and statistical significance, but the differences are not such that they warrant different conclusions. I use total debt in the tables and analysis where nothing else is stated. Bowman (1980) studies the association between systematic risk and book and market leverage measures. Bowman finds that the book value of debt and the market value of debt are statistically indistinguishable from each other. So, apart from the practical difficulties of obtaining high quality price information on non-traded debt, the use of book value should only have a minor impact on the results. This choice of book values over market values of debt only matters if the company is in trouble or if the loan has a different interest than the prevailing market rate. These two situations can bias the market values of debt up or down.

From a practical point of view it is assumed that firms do not implement the trade-off instantaneously, but tend to strive towards the optimal trade-off point over time. I test for the trade-off model in a two-stage regression. The first stage regression gives coefficients for calculating optimal leverage for the second stage regression. The second stage regression is used to test for any mean reversion against the optimal leverage.

The first stage regression also gives information on the validity of the trade-off theory. The independent variables are proxies for factors that should influence the optimal trade-off. Insignificant proxies are a sign that the trade-off theory does not describe firm leverage. The first stage regression follows

[15] Defined as the book value of debt divided by the sum of the market value of equity and book value of debt.

Hovakimian et al. (2001) and Fama & French (2002) in the choice of proxies. The observed leverage ratio is regressed on proxies for the tax shield, non debt tax shield, growth options, and bankruptcy risk that have been important in earlier cross-sectional studies of capital structure decisions. I group the proxies into four groups with similar attributes. The over all attributes are i) Profitability, ii) Non-debt tax shield, iii) Growth options, and iv) Volatility of earnings.[16] Now, the setup is closely based on earlier tests of mean reversion. There are some issues that needs to be pointed out, the proxies that have been used in other studies are not necessarily the ones that best describe the optimal capital structure and there is a problem in that some variables are related by construction.[17] Specifically, there are successful studies on bankruptcy prediction using accounting data, see Altman (1968), Ohlson (1980) and Skogsvik (1988). The relation by construction means that the dependent variable is a direct function of the independent variables. This method for determining the (unknown) optimal leverage has significant problems, but to enhance the comparability with other studies I use the same proxies.

The motivation for the attributes is as follows; (i) firms with high profitability have both a higher probability of using the entire tax shield and higher earnings to shield from taxes. Given that the tax shield argument is valid higher profitability should give high leverage, a positive association. (ii) DeAngelo & Masulis (1980) argue that firms with more non-debt tax shields substitute away debt and have less leverage. (iii) Myers (1977) argue that a firm's growth options is negatively correlated with the capital structure. Firms with more growth options do not want to risk these in a bankruptcy and have less leverage. (iv) Firms with higher bankruptcy risk should have less leverage, since leverage is positively correlated to bankruptcy. The bankruptcy risk is approximated by volatility of earnings. Fama & French (2002) argues that larger firm have less volatility in earnings so that this attribute can be approximated with firm size.

As Titman & Wessels (1988) point out, there are a number of problems with the attribute setup. There might not be good proxies for the attributes and the use of imperfect proxies introduces an error-in-variables problem.

[16] The 'net loss carry forward' that I would have wanted is unfortunately not available for my data set. It could have given information on the value of the tax shield.

[17] To illustrate the problem consider a simple equation with one dependent and one independent variable. The dependent variable is leverage ($\frac{D}{A}$) and the dependent variable is market-to-assets ($\frac{M}{A}$). The sum of market value of equity and debt is the assets ($M+D=A$). The independent and the dependent variables sum to one ($\frac{D}{A}+\frac{M}{A}=1$). Now it is known that the equation $\frac{D}{A}=\alpha\frac{M}{A}$ has an exact solution. The solution is $\alpha=\frac{D}{M}$. The relationship is not linear, but the explanatory value (R^2) for a regression between the dependent and the "independent" variables should be high.

Table 3.4. Attributes and proxies

Attribute	Proxy	Predicted sign
Profitability	Earnings/Assets	+
	Three year mean operating earnings/ Assets	+
Non-debt tax shield	R&D/Sales	-
	Depreciation/Assets	-
Growth options	Market-to-book	-
	Market-to-Assets	-
	R&D/Assets	-
	Stock returns	-
Volatility of	Log of Assets	-
earnings	Fixed Assets/Assets	-
	Industry	

The proxies are collected in vectors f_t and the coefficients are assumed to be stable over time. The coefficients are estimated on the current leverage for each firm, as in Hovakimian et al. (2001).

$$(D/A)_{j,t} = \alpha_j + \beta_j f_{j,t} + \varepsilon_{j,t} \tag{3.2}$$

I use the estimated coefficient from regression (3.2) to determine the optimal leverage for each firm j for the next period. The specification can also be applied to sectors or the entire sample. It can be expected that there is multicollinearity in some of the parameter estimates. The size of the individual parameter is of no importance but only the total predictive ability for the value of the optimal capital structure for the next period.

The problems with the first stage regression can be summarized as i) the aim is to predict an unobservable variable and there is no way of evaluating if it has been successful, ii) the independent variables are by construction related to the dependent variable, and iii) the proxies might not proxy the optimal leverage. As it turns out, the predicted optimal leverage used in the second stage regression is typically close to the current leverage, meaning that the first stage is not so useful. The first stage predicted values are kept to make it possible to compare with other studies. In the later test for trade-off and historical chance, the predicted optimal leverage is dropped in favor of a simple mean.

In the second stage regression the predicted optimal ratio is regressed on a mean-reversion process. The optimal ratio is predicted using the coefficients on the factor from equation (3.2). According to the trade-off theory there is an optimal leverage. The optimal leverage ratio is an unknown and unobservable. Instead of the true optimal leverage, I use a predicted value based on the cross-section of firms. The underlying assumption necessary to test for reversion to the optimal leverage is that firms make the correct choices of leverage in the cross-section. If there is a mean-reversion with drift (α_j) it will be visible in the gamma estimate. The test is slightly problematic in that the target (optimal leverage) changes over time and the optimal leverage is (implicitly) deducted in the dependent variables. In the tests this potential problem is ignored since the changes in optimal leverage change little from time period to time period.

$$\left(\frac{D}{A}\right)_{j,t+1} - \left(\frac{D}{A}\right)_{j,t} = \alpha_j + \gamma_j \left[\left(\frac{D}{A}\right)_{j,t} - \left(\frac{D}{A}\right)^*_{j,t}\right] + \eta_{j,t}, \tag{3.3}$$

where the star indicates the optimal level of debt-to-assets. The gamma parameter is the speed of mean reversion in capital structure and it measures how much of the difference between the current and the optimal leverage that is eliminated in each period. The speed of mean reversion is in this test assumed to be fixed over the sample period. As a stability measure I will also test the industry sub-samples. If the estimated gamma is between minus two and zero, leverage is converging to a long run mean. The specification in equation (3.3) can be re-written in random walk form. Testing if γ is significantly different from zero is equivalent to testing for a unit root in a random walk setting.[18] I calculate Dickey-Fuller t-statistic critical values[19] and use these critical values in the significance testing.

The validity of the mean reversion test can be questioned. Since the determinants of the optimal leverage do not change much from year to year, the error and the change in leverage are similar. This similarity makes it hard to reject a mean-reversion, giving a weak statistical power to the test as is found by Shyam-Sunder & Myers (1999). Even if the test statistics seem strong, the test is not as strong as the t-statistics indicate. The test uses in-sample coefficients, which means that if there are changes in the determinants of the optimal leverage, then the prediction for optimal leverage will be wrong. The optimal leverage cannot be observed. The fact that the actual leverage is fairly close to the predicted optimal leverage and approaches it does not guarantee that the mean reversion is towards an actual optimal leverage. The third problem with the estimation is that many of the parameters are related by construction. An econometric issue is that the tests presuppose long time series, but the series are very limited in length, with a maximum of 15 observations for each firm. An alternative test is developed in Appendix 3.D. This

[18] $H_0 : \gamma_j = 0 \,\forall\, j,\ H_1 : \gamma_j < 0 \,\forall\, j$

[19] The Dickey-Fuller test can be found in advanced text books on econometrics such as Hamilton (1994).

alternative test is a difference test, so it is stronger in the sense that it more easily rejects mean reversion, i.e. the slow moving leverage does not make the test more likely to accept mean reversion. The alternative test makes use of panel data, so it relies less on the length of the times series. The test is slightly different for instance in that it assumes a common mean reversion parameter for the tested groups.

Fama & French (2002) raise the issue that the normal OLS standard errors from the second equation ignore the firm cross-sectional variation in parameter estimates in the first equation. I use the in-sample distribution of the mean-reversion parameters to remedy this problem and to get estimates of the standard errors for the second stage regression in the spirit of Fama & MacBeth (1973). Using this set-up it is possible to reject the first claim. Even if the mean reversion cannot be rejected, it is not certain the trade-off is the best description.

Testing the pecking order theory

The pecking order theory predicts that firms with excess internal funds in relation to changes in their operating net assets (ONA) take different actions than firms with deficits in internal funds. Firms with excess internal funds are predicted to finance their growth in operating net assets with internal funds. Firms with deficit in internal funds are expected to increase their debt. I divide the sample into firm with excess internal funds and firms with a deficit in internal funds, and test if I can reject the hypothesis in favor of the pecking order theory. After this, two additional tests are introduced where the firms have sticky dividend policies. The idea is then that firms adjust their dividends slowly and thus firms with excess earnings will have greater ability to finance their changes in ONA, and similarly unlucky firms will have a greater reliance on debt.

The pecking order behavior among firms can be observed when there is a deficit in internal funds. The first set of tests focuses on the financing of changes in operating net assets (ΔONA), change in net financial debt (ΔND), earnings (X) and dividends (d). Operating net assets is defined as the difference between all non-financial assets and all operating debt. Net financial debt consists of all non operating debt, such as short and long term borrowing, lease obligations, and financial assets.

Firms with a surplus, i.e. when ($\Delta ONA \leq X$), will according to the pecking order theory, use internal funds to finance changes in ONA. This gives the hypothesis for testing the pecking order:

$H_0 : \Delta\left(ONA_{t,j}\right) - \left(X_{t,j} - d_{t,j}\right) > 0,$

since the change in equity should at least match the change in ONA. The subscripts represent time period (t) and company (j). The later tests are tests against the competing hypothesis (pecking order) for all hypotheses. If H_0 is rejected, this supports the pecking order since firms then tend to use only the internally generated funds $(X - d)$ to finance deficits in ONA.

Firms with deficits, i.e. when $(\Delta ONA > X)$, must finance the expansion in ONA by acquiring outside capital. According to the pecking order the next source of capital when the internal funds do not suffice is debt. Given that the firms have a deficit, then the alternative to the pecking order theory would be:

$H_1 : \Delta\left(ND_{t,j}\right) - \left(\Delta\left(ONA_{t,j}\right) - X_{t,j}\right) < 0.$

If H_1 is rejected the pecking order hypothesis would be supported.

The historical chance and pecking order can be jointly tested by adding an assumption of sticky dividends. The lagged dividend is used to predict the future dividend. The lucky firms will have a surplus also after fulfilling the implicit dividend contract with the share holders. Adapting the hypotheses (H_0 and H_1) for firms with sticky dividends, given that there is a surplus in internal financing $(\Delta ONA_{t,j} \leq X_{t,j} - d_{t-1,j})$, implies that:

$H_2 : \Delta\left(ONA_{t,j}\right) - \left(X_{t,j} - d_{t-1,j}\right) > 0,$

and for firms with a deficit in financing:

$H_3 : \Delta\left(ND_{t,j}\right) - \left(\Delta\left(ONA_{t,j}\right) - \left(X_{t,j} - d_{t-1,j}\right)\right) < 0.$

The tests of these hypotheses are done for all companies with a sufficient number of observations. Note that firms can have both surpluses and deficits in the sample, and thus be present in all the tests of H_0 through H_3. The outcome of the tests is presented in pooled form. The pooling is done after the statistics have been scaled with ONA_t.[20]

The idea that firms with inadequate internal funds for investments in real assets and dividends issue debt has been tested before. The second test follows Shyam-Sunder & Myers (1999) and is done in a two-step procedure. First the deficit in internal funds is calculated and then this value is related to changes in debt. The internal funds are measured as the operating profit less taxes, interest costs and net investment in property, plant, and equipment. I then

[20]The same tests have been run with total assets as scaling factor without any notable difference in results.

calculate the deficit for each firm as:

$$DEF_t = d_t + CX_t + \Delta W_t + R_t - C_t, \tag{3.4}$$

where DEF is the calculated deficit, d is the dividend, CX is capital expenditures, ΔW is change in working capital, R current portion of long term debt at the start of time period t, and C is the operating cash flow after interest cost and taxes.

The claim that the deficit is related to changes in debt is operationalized through the following test:

$$\Delta D_{i,t} = \alpha_i^{po} + \beta_i^{po} DEF_{i,t} + \varepsilon_{i,t}, \tag{3.5}$$

where the pecking order prescribes that the intercept (α^{po}) is zero and the coefficient (β^{po}) is one.

The trade-off theory and the historical chance

If there is a historical chance in the cross-section, it can be visible in the estimation of equation (3.2)(p. 121). The predicted sign of the coefficient of profitability should be positive for the trade-off theory, but negative for historical chance.

The main difference between the two theories should be possible to discern over time, the better performing firms should accumulate equity over time and have less leverage. The trade-off suggests that better performing firms should distribute dividends and/or increase the volume of outstanding debt to maintain the optimal leverage. This means I can test for a trade-off against historical trends[21] in leverage.

The cross-section of firms in my sample makes it possible to test mean reversion and trends. The test will focus on this rather than how the optimal leverage changes. The setup to calculate optimal leverage in equations (3.2) and (3.3) does not yield much different estimates than a simple mean. The next test will thus be based on a simpler model:

$$L_{j,t+1} - L_{j,t} = \alpha_j + \beta_j \left(L_{j,t} - \bar{L}_j\right) + \delta_j t + u_t \;\; \forall j, \tag{3.6}$$

where $L_j = \frac{D_j}{A}_j$ is leverage for firm j in period t, and $\bar{L}$ is the average leverage of the firm during the entire sample. The use of the entire sample for the mean, means it will be harder to reject the mean reversion. The idea is to

[21] A trend can be defined as: $X_t = \alpha + \delta t + \epsilon_t$, where α and δ are coefficients and t time and ϵ an error term; a linear function over time.

test if firms exhibit mean reversion in the beta, or if firms have a strong trend coefficient in the delta. When the beta coefficient is between zero and minus two there is mean reversion. The method for joint tests of mean reversion are outlined in Appendix 3.C.

3.4 Results

3.4.1 Testing for the trade-off theory

Starting with the entire sample, the parameters of equation (3.2)(p. 121) are presented in Table 3.5 (and appendix 3.E Table 3.E.1) below. I report the tests of the individual attributes and the total for both tables. The reason this step-wise approach is done is to show that there is information in all the groups of attributes, and that when the attributes are combined they do not change the parameter estimates.

Table 3.5. Regressions for predicting debt-to-asset (market) ratio.

Proxy	Profitability		Non-Debt Tax-Shield		Growth Options		Volatility of Earnings		All Attributes	
Constant	0.53	***	0.42	***	0.81	***	0.53	***	0.89	***
Earnings/Assets	-1.47	***							-0.58	***
$\overline{op.earnings}$/Assets	-0.29	***							-0.33	***
R&D/Sales			-1.65	***					-0.21	
Depreciation/Assets			1.23	***					-0.82	***
Market-to-Book					-0.03	***			0.00	**
Market-to-Assets					-0.65	***			-0.46	***
R&D/Assets					-1.64	***			-0.24	
Stock Returns					0.00	*			0.00	*
Log of Assets							-0.03	***	-0.01	***
Fixed Assets/Assets							0.36	***	-0.06	***
R^2	0.23		0.13		0.72		0.27		0.61	
$\overline{R}^2$	0.23		0.13		0.72		0.27		0.60	
Nr Obs.	883		1110		998		1140		766	

$(D/A)_{j,t} = \alpha_j + \beta_j f_{j,t} + \varepsilon_{j,t}$

The Market-to-Book is the market value of equity divided by the book value of equity, the Market-to-Assets is the market value of equity divided by the book value of assets, and the Stock Return is the return on a share held since the preceding year. The coefficients are from a standard OLS regression. (The coefficients have been compared to a censored tobit regression and only differ slightly in the t-statistics.) The asset values are calculated using the market value of equity. $\overline{Op.earnings}$ is the average operating earnings over three years. Observations lacking data points have been dropped. $\overline{R}^2$ is the adjusted R^2. Coefficients significance levels are marked with ***,**, and * for 1%, 5% and 10% levels.

The coefficients for earnings and average operating earnings are negative. This negative result is surprising since the tax shield argument predicts a positive association. The volatility of earnings is significant. The market value based estimates do explain more of the variation in leverage, as measured by the $\overline{R}^2$

than the book value based measures in Table 3.E.1. The significance levels are high in general, but the market value based regressions suffer from the problem of relation by construction between the dependent variable and the independent ones. The denominator is in many cases the market value of assets and if the market value of equity increases, the denominator increases for both the dependent and the independent variables.

For the calculation of optimal leverage using the market value of equity, the results are similar to the book value based calculations. I have calculated the average impact of each variable for the market based optimal leverage.[22] The four variables with most impact are Market-to-Assets, Market-to-Book, Earnings and the level of Fixed assets. This is not surprising since the market leverage is related by construction as mentioned in econometric section.

The R&D scaled by assets is dropped when I calculate the predicted value for the second stage regression. The reason is that R&D scaled by assets is co-linear with the R&D scaled by sales.

It is conceivable that different industries have different capital needs or risks, so testing if industry matters for the results is the next step. There are missing data points, and a fair number of firms have not been listed for a sufficient number of years to yield company specific estimated coefficients. The industry coefficients are used to determine the optimal leverage for each firm. The estimates are provided in Table 3.E.2. The industry coefficients are multiplied with the parameters for each firm. The exceptions are the Oil&Gas and Telecommunications where the coefficients for the entire sample are used since there are not sufficient data points to determine industry coefficients.

The results from the mean reversion tests in Table 3.6 below are for the entire sample and the different industries. The book value based estimates are presented as well. To estimate the t-statistics for the parameters I have used the sample distribution of parameters. The normal standard errors from the second stage regression do not include the uncertainty from the first stage regression, as mentioned above.

[22] The impact is the average explained share of the predicted value of each coefficient.

Table 3.6. Test of Mean Reversion by industry.

	Market Value Based						Book Value Based					
Industry (ICB)	Constant		Mean Reversion			Nr Obs.	Constant		Mean Reversion			Nr Obs.
All Firms	-0.01	-0.1	-0.25	-14.6	***	1007	-0.01	-0.1	-0.41	-12.2	***	1192
Oil & Gas	-0.01	-0.1	-0.53	-102.6	***	12	0.00	0.0	-0.83	-36.4	***	12
Basic Materials	-0.02	-0.2	-0.31	-19.7	***	147	-0.01	-0.1	-0.29	-34.3	***	174
Industrials	-0.01	-0.1	-0.28	-14.2	***	456	-0.00	-0.0	-0.32	-10.4	***	542
Consumer Goods	-0.01	-0.1	-0.09	-7.4	***	99	-0.01	-0.1	-0.24	-16.4	***	112
Health Care	-0.00	-0.1	-0.24	-33.1	***	42	-0.05	-0.3	-0.90	-7.7	***	52
Consumer Services	-0.02	-0.2	-0.11	-15.0	***	53	-0.03	-0.2	-0.29	-17.2	***	64
Telecommunications	-0.02	-0.5	0.14	30.2		4	-0.05	-0.9	0.03	2.6		7
Utilities	-0.01	-0.1	0.12	16.9		25	-0.05	-0.3	-0.55	-23.2	***	35
Real Estate	-0.00	-0.0	-0.37	-21.7	***	82	-0.01	-0.1	-0.22	-11.1	***	103
Technology	-0.02	-0.1	-0.24	-12.7	***	87	-0.02	-0.2	-0.36	-18.9	***	91

$$\left(\frac{D}{A}\right)_{j,t+1} - \left(\frac{D}{A}\right)_{j,t} = \alpha_j + \gamma_j \left[\left(\frac{D}{A}\right)_{j,t} - \left(\frac{D}{A}\right)^*_{j,t}\right] + \eta_{j,t}$$

The mean reversion coefficient is the (γ) from equation (3.3). The t-statistics are calculated from the sample distribution of the respective parameters. Coefficients significance levels are tested against single sided (case 4) Dickey-Fuller critical values and marked with ***,**, and * for 1%, 5% and 10% levels.

The adaptation process towards the optimal capital structure appears to be reasonably fast.[23] For the book-value based sample the change in leverage between two years eliminates 41 percent of the deviation from the optimal leverage. The market value based sample has a slower adaptation process, where 25 percent of the difference is eliminated each year. For the all firms sample the explained variation measured by R^2 is 26 percent and 9 percent for the book and market value based samples. This result is consistent with the finding in Welch (2004) that firms only partially adapt their capital structure when equity valuation changes. Claim 3.1 operationalized through mean reversion cannot be rejected from the results in Table 3.6. Simulated Dickey-Fuller t-statistics are available in Appendix 3.F.

The mean reversion parameters differ between industries. The trade-off theory is supported by the results in most dimensions being tested (all firms, industry, book value, and market value based samples). The negative value of the constant indicates that the leverage is decreasing over time. The effect is strong in both the book-value based and the market value based estimates. Most industries, except telecommunication, have converging mean reversion coefficients (γ) for book-values. The market value based sample has two industries with parameters that do not mean revert. The result supports mean reversion, meaning that the hypothesis of mean reversion can not be rejected,

[23] If the mean reversion parameter belongs to $[-1, 0)$ there is a smooth mean reversion and if the parameter belongs to $(-2, -1)$ there is an "overshooting" process that converges. If the parameter is positive then the observed leverage diverge from the optimal leverage. The process is trend stationary if $\gamma \in (-2, 0)$.

since most industries have statistically significant and converging mean reversion parameters.

The test of the trade-off theory exhibits at least one of the problems mentioned earlier. The column for 'Growth options' in Table 3.5 explains much of the variation in leverage, as could be expected from the relation by construction. To some extent this carries over into the estimates with 'All attributes'. The high level of explained variation in Table 3.5 gives false comfort as to how well the optimal leverage is described by the first stage regressions.

Since there are some statistical issues with the test in Table 3.6, an alternative test is constructed in Appendix 3.D. The conclusions from the alternative test in Table 3.D.1 are weaker than the conclusions from Table 3.6, but that the null hypothesis of no mean reversion can in most cases be rejected. Given these problems, the results supports mean reversion in capital structure. The question is if there are better explanations around.

3.4.2 Testing for the pecking order theory

The four hypotheses of the pecking order theory are tested for all companies. The tests of the hypotheses are presented in Table 3.7.

Table 3.7. Testing hypotheses for the Pecking order theory.

Number	Mean	Std	T-stat	Observations
H_0	-0.22	0.36	-0.61	601
H_1	-0.02	0.14	-0.15	348
H_2	-0.17	0.38	-0.46	519
H_3	-0.02	0.14	-0.17	422

For each hypothesis the relevant sample is pooled. The t-statistic is the a test if the mean deviates from zero in the pooled distribution.

The the first hypothesis (H_0) for firms with a surplus ($\Delta ONA \leq X$) cannot be rejected, meaning that the pecking order hypothesis is not supported. The second hypothesis (H_1) for firms with a deficit ($\Delta ONA > X$) can not be rejected either. The pecking order does not have the strength to replace the alternative.

The combination of the alternative to the pecking order with the sticky dividends concept (H_2 and H_3) does not help the pecking order, it can still not supplant the alternative.[24] In total, the pecking order get no support from these tests.

The second test is suggested in equation (3.5)(p. 125) with a scaling factor of book assets. Shyam-Sunder & Myers (1999) states that the pecking order

[24]In unreported tests with the pecking order as the null hypotheses, it is rejected in four pooled tests.

theory prescribes a beta coefficient for the deficit of one. However, it should be noted that if firms choose debt over equity with the ratio one, the cross-sectional average leverage has to go up over time. That is, the coefficient from the test is approximately equal to the marginal leverage ratio. If the coefficient is less than the average ratio in the sample, the leverage is decreasing and vice versa.

The leverage ratio for US firms has been increasing from 1971 to 1989 according to the descriptive statistics of Shyam-Sunder & Myers (1999) and Frank & Goyal (2003). This could be caused by the influence of the pecking order theory. However, a higher level of debt in new financing choices makes the suggested test more likely to accept a null hypothesis of pecking order. Likewise, a sample with a low level of debt in new financing choices makes the test more likely to reject the pecking order theory. For Swedish firms from 1990 to 2004 the leverage is decreasing on average. From this decreasing leverage I would expect much weaker support for the pecking order theory, since the average leverage of new financing is lower than the current leverage. The lagged deficit has been included and tested, since it has had strong explanatory power on US data. This weaker support in my Swedish sample for the pecking order theory can be seen in Table 3.8.

Table 3.8. Debt deficit finance test of the Pecking order.

	Deficit and surplus						Deficit only					
Variable	Coeff.	t-stat		Coeff.	t-stat		Coeff.	t-stat		Coeff.	t-stat	
Constant	-0.05	-6.0	***	0.04	3.7	***	-0.11	-11.7	***	0.04	3.4	***
DEF_t	0.47	24.0	***				0.60	28.3	***			
DEF_{t-1}				0.07	3.0	***				0.07	2.6	***
$DEF_t - DEF_{t-1}$				0.41	15.6	***				0.46	16.6	***
Nr Obs.	1142			981			984			852		
R^2	0.34			0.20			0.45			0.24		
$\bar{R}^2$	0.33			0.20			0.45			0.24		

$\Delta D_t = \alpha^{po} + \beta^{po} DEF_t + \varepsilon_t$

The deficit is calculated as $DEF_t = d_t + CX_t + \Delta W_t + R_t - C_t$,where DEF is the calculated deficit, d is the dividend, CX is capital expenditures, ΔW is change in working capital, R current portion of long term debt at the start of time period t, and C is the operating cash flow. The t-statistics are the standard OLS t-statistics. Coefficients significance levels are marked with ***,**, and * for 1%, 5% and 10% levels.

For the Swedish sample the explanatory power is clearly in the current period. The poor power of the lagged deficit indicates that there is no strong trend in the deficits of the firms. The current deficit is financed on average by 47 percent from new debt, well below the average book leverage of 63 percent (see Table 3.2). The deficit finance test has a higher share of debt financing if only deficit observations are included. However, this (0.60) is also below the average leverage, so the decreasing trend in leverage is driven both by firms with and without deficits.[25]

The coefficient estimates differ from what has been found on US data. The reason is that Swedish leverage is decreasing during the sample period, as opposed to the US test where leverage has been increasing. The explained variations for the tests are lower than what Shyam-Sunder & Myers (1999) find on US data, but in line with Frank & Goyal (2003) found in their US sample.

When firms need outside capital the pecking order theory prescribes that firms should prefer to issue debt. From Table 3.8 it seems like the companies listed on the SSE main list cannot acquire new debt even though the leverage is *decreasing* during the sample period, or that firms do not prefer to issue debt. Either the pecking order theory is a poor description of firm behavior or firms are off-equilibrium. Testing the coefficient against the null hypothesis of the pecking order ($\beta^{po} = 1$) leads to a rejection of the pecking order theory (Students t-statistics are 50 and 46 for the coefficients of DEF_t being different from one). There is no support for the pecking order in the second test for the Swedish sample.

Summing up the tests of the pecking order theory there seems to be some support for firms choosing to use internal funds for expansion. It is possible that the trend in leverage has influenced the results for the pecking order, both in my Swedish sample and in the US studies. If leverage is decreasing year by year, as in Sweden, then it is feasible that the trend in leverage wipes out any trace of the pecking order. The non existing support for the pecking order and the strong mean reversion results from the trade-off theory section has given an answer to how firms tend to choose their leverage. The confounding factor for the trade-off theory is the trend. The trend is a prediction from the historical chance. In the next section the historical chance aspect of the pecking order theory will be tested against the trade-off.

3.4.3 Historical chance or trade-off?

From the results in Table 3.5 and Table 3.E.1 there is some support for a historical chance interpretation in that the leverage is strongly negatively related to earnings in both tables. The movement toward the "optimal" leverage point seems strong, but is the movement mean reversion or only inertia?

To separate the trade-off from the historical chance I use a regression with both a mean reversion parameter and a trend parameter, as described in

[25]The leverage for the Swedish firms is decreasing during the sample period, as can be seen in Figure 3.2 in Appendix 3.A.

equation (3.6)(p. 125) for each firm in the sample. The idea is to see if either the mean reversion or the trend parameter eliminates the other.[26]

The Wald statistics are constructed in a two step procedure. First I run one regression for each firm in the sample, in accordance with equation (3.6). After that the hypotheses are used to calculate the Wald statistic as in equation (3.8)(p. 142) for each line reported in Table 3.9. I exclude firms with four or less observations. One example of a hypothesis is the mean reversion parameters for all Basic Material firms are jointly different from zero. The same test is then performed for the other industries, the market value based sample, and all firms.

Table 3.9. Wald tests for mean reversion and trends by industry.

	Market Value Based			Book Value Based		
Industry(ICB)	Mean Reversion	Trend	N	Mean Reversion	Trend	N
All Firms	-0.89 ***	-0.01 ***	108	-0.76 ***	-0.01 ***	125
Oil & Gas	-0.43	0.00	1	-0.30	0.00	1
Basic Materials	-0.87 ***	-0.01 ***	16	-0.69 ***	-0.01 ***	19
Industrials	-0.87 ***	-0.01 ***	48	-0.66 ***	-0.01 ***	55
Consumer Goods	-0.70 ***	-0.03 ***	10	-0.84 ***	-0.01 ***	11
Health Care	-1.06 ***	0.00 ***	5	-0.86 ***	-0.01 ***	6
Consumer Services	-1.04 ***	0.01 ***	7	-1.04 ***	-0.00 ***	7
Telecommunications	-0.77 *	-0.03 ***	1	-0.41	-0.02 *	1
Utilities	-1.00 **	-0.01 ***	3	-0.87 ***	-0.02 ***	4
Real Estate	-1.00 ***	-0.01 ***	8	-0.83 ***	-0.01 ***	12
Technology	-0.99 ***	0.00 ***	9	-1.04 ***	-0.01 ***	9

This table presents the mean coefficients for industries for joint tests of the mean reversion or trend parameters of the different samples. Robust standard errors are used in the calculation. The test setup requires the capitalization choice of firms to be independent from the choices of other firms. The mean reversion parameter is tested against a simulated Dicky-Fuller distribution for joint test of several mean reversion parameters. N is the number of firms present in the tested industry. Firms with less than four observations are excluded from the sample. Coefficients significance levels are marked with ***,**, and * for 1%, 5% and 10% levels.

In light of the strong results from previous trade-off tests it is not surprising that the Wald test cannot reject the mean reversion parameter for the entire sample and most industries. The coefficients differ for each firm, but the mean of the mean reversion parameter is -0.89 and -0.76 for the market value and book value based all firms samples. The trend parameter for all firms is -0.01 for both the book value and market value based samples. The industry based samples are of similar size to the over all sample. The mean reversion is statistically significant in both the market and the book value based samples.

[26]In these tests I have used robust standards errors since the errors seems to be heteroscedastic when examined. There does not seem to be any noticeable autocorrelation. Even so, I have tested the Newey & West (1987) one lag standard errors without any major difference in significance.

The trend is also statistically significant. The inclusion of the trend coefficient also increases the speed of mean reversion, as could be expected. Both the mean reversion and the trend are thus important in determining the capital structure in the industry based sample. There is not necessarily a clear cut difference between the two, but it is not unlikely that part of the strong results in the trade-off section were due to a strong trend in leverage choices. It is possible that the trend is actually a result of the optimal leverage shifting each year towards a lower leverage for the largest Swedish firms. The results in Table 3.9 suggest the best description for leverage choice is a mean reversion with trend process.

The idea with historical chance is not only that firms should have trends in their leverage choices, but also that the trend should be stronger for more profitable firms or unprofitable firms. To test this idea, I divide the sample in three groups of equal size, the high, normal and low average profitability in sample.[27] These three groups are then tested using the same methodology as for the tests in Table 3.9 and the results can be found below in Table 3.10.

Table 3.10. Wald tests for mean reversion or trends by profitability.

	Market Value Based				Book Value Based			
Profitability	Mean Reversion	N	Trend	N	Mean Reversion	N	Trend	N
High	-0.85 ***	44	-0.01 ***	44	-0.79 ***	43	-0.01 ***	43
Normal	-0.98 ***	30	-0.01 ***	30	-0.73 ***	43	-0.01 ***	43
Low	-0.88 ***	34	-0.00 ***	34	-0.75 ***	39	-0.01 ***	39

This table presents the mean coefficients for profitability groups for joint tests of the mean reversion or trend parameters of the different samples. Robust standard errors are used in the calculation. The test setup requires the capitalization choice of firms to be independent from the choices of other firms. The mean reversion parameter is tested against a simulated Dicky-Fuller distribution for joint test of several mean reversion parameters. N is the number of firms present in the tested profitability group. Firms with less than four observations are excluded from the sample. Coefficients significance levels are marked with ***,**, and * for 1%, 5% and 10% levels.

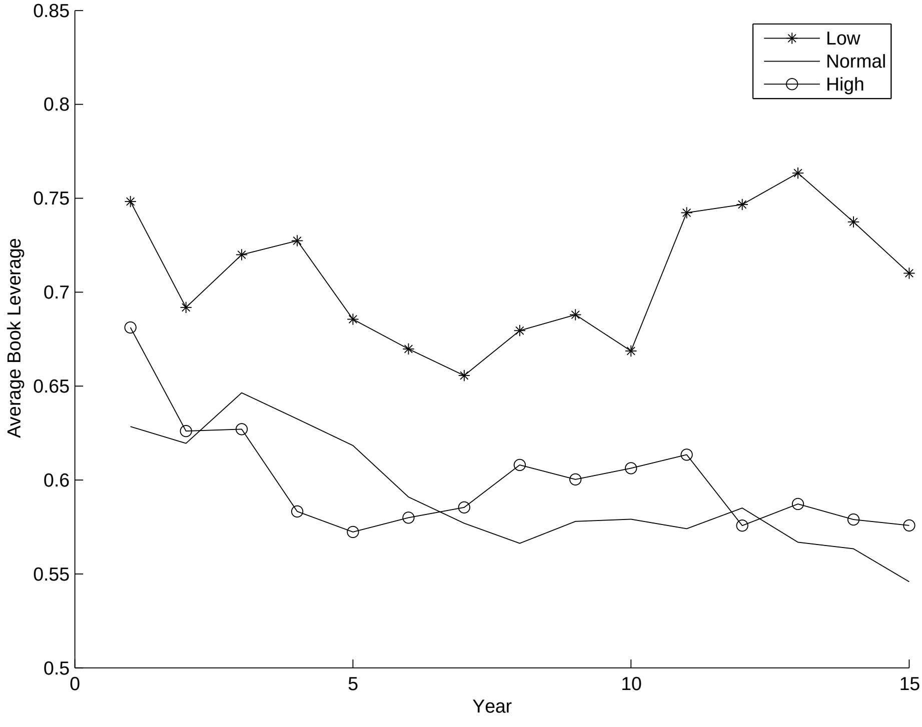
The results from the overall sample are confirmed on the profitability ranked sample. The parameter estimates are very similar for all three groups. The mean reversion parameter ranges from -0.85 to -0.98 for the market value based sample and from -0.73 to -0.79 for the book value based sample. The trend parameter is about -0.01 for all tests. The parameter estimates are similar for all three profitability groups. There is no difference if the analysis is based on the book or the market value of equity. The null hypotheses of no mean reversion or no trends are rejected.

In Figure 3.1 below the trends of average leverage are depicted. The series all start at year one for each firm and show the average leverage in each group

[27] The division is done only in-sample due to data limitations. Dividing the sample in half for instance would leave an average of five data points per firm over time to use for testing.

up until year fifteen. Firms with shorter series are included in the calculations only for the number of years they participate in the sample.

Figure 3.1 The Average Leverage for profitability groups.



The leverage of the low profitability group is higher than the normal and high profitability groups. All three series show a decreasing leverage over the first part of the graph. In the second part of the graph the low profitability firms have an increasing average leverage.

Both the mean reversion and trend components are strong in the sample. The relation between profitability and leverage seems stronger for low profitability firms. In Figure 3.1 the high and normal profitability firms end up having similar leverage after a few years. The low profitability firms are more constrained in their leverage choices.

3.5 Conclusion

In the tests for mean reversion there is statistical support for the mean reversion (Table 3.6, Table 3.9, Table 3.10 and Table 3.D.1). However, the high adjustment speeds coupled with a slow moving trend does not make sense in terms of a trade-off perspective. It is unclear why there is a trend from a mean-reversion perspective, and it is not impossible that each firm tries to attain a capital structure target, but that the aggregate has a strong trend component.

The study of the Swedish sample reveals a few shortcomings in how the pecking order is studied. At least in the Swedish sample, the influence of the trend in the aggregate change in capital structure is much stronger than the pecking order. Disregarding the strong over-all performance for the Swedish firms, the notion that the marginal deficit should contain information in the pecking order theory is not validated.

The pecking order has statistical support in the historical chance aspect, the return on equity is related to the leverage. There is also a clear trend in the data. The return and leverage relationship has clearly not changed since Bertmar & Molin (1977) studied it. However the situation is a bit different, firms now tend to decrease their leverage, so the firms as an aggregate generate more funds than they need for expansion. In short the second claim can be rejected, but not the third. Firms' competitiveness and profitability seem to have an influence on their capital structure.

The pecking order does less well on its own in the direct tests (Table 3.7 and Table 3.8), on internal financing and deficit financing, than in the indirect tests (Table 3.9 and Table 3.10). The marked difference in strength between the asymmetrical information based predictions and the historical chance imply the pecking order is not a good description of firm behavior after all. The support for the trend indicate there are more mundane relations than the pecking order theory. It is most likely not too important how firms choose their capital structure within reasonable bounds. The firms expand slowly and retain an excessive share of their earnings. The observed capital structures depend more on how successful firms have been in their past operations than they are an outcome from a pecking order.

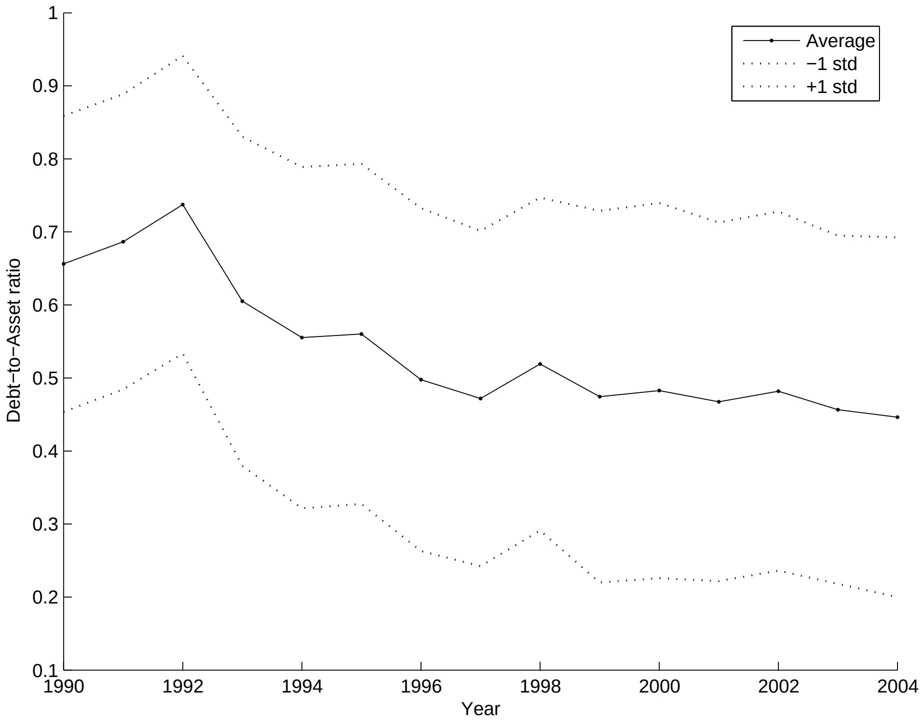
3.A Appendix - Economic development in Sweden

3.A.1 The sample period

In this appendix, I will give a brief overview of how the parameters of interest have changed over time, and briefly note some of the underlying factors for these changes. It is not a presentation of the Swedish economy during the sample period. For a description of this see for instance Henrekson & Jakobsson (2003).

The average leverage ratio has been decreasing over time, with a notable exception in 1992. In 1992 the cross-section of large Swedish firms was doing very poorly due to uncompetitive prices and a fixed currency exchange rate. The currency peg was dropped in 1992. The decreasing leverage implies debt is

Figure 3.2 Debt-to-assets (market) over time.



used to a lower degree in new financing in comparison to the current financing. Firms in the sample tend to use a higher proportion of equity than debt for new financing. This negative slope of the leverage is in contrast to U.S. data where the proportion of debt has been increasing according to, for instance, the descriptive statistics of Shyam-Sunder & Myers (1999).

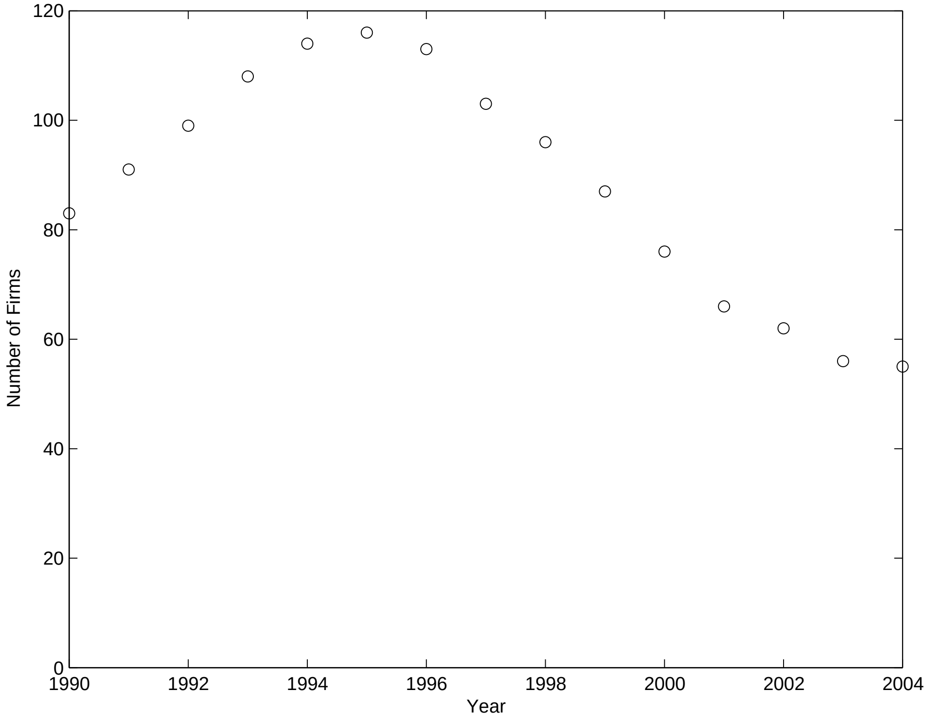
The spread of leverage (the dotted lines is one standard deviation up and down around the mean) in Figure 3.2 has increased somewhat over the sample period. The lower leverage in itself should give a lower return on equity, but this can not be found in Figure 3.3 below. The fairly stable level of ROE in

Figure 3.3 Sample Returns over Time.

Figure 3.3 is slightly surprising, since leverage is decreasing during the sample period. ROE is a function of $ROA, COD,$ and $\frac{D}{E}$. If leverage had remained the same the ROE would have increased. Instead the firms have retained capital and decreased leverage. The asset expansion can be seen in Figure 3.5. The firms have increased their assets, decreased their financial leverage, and kept their return on equity, so the cost of debt have decreased. The firms have not only been able to finance their asset expansion, but also decreased their leverage.

During the sample period an inflationary target for the central bank has been introduced, lowering the inflation substantially.

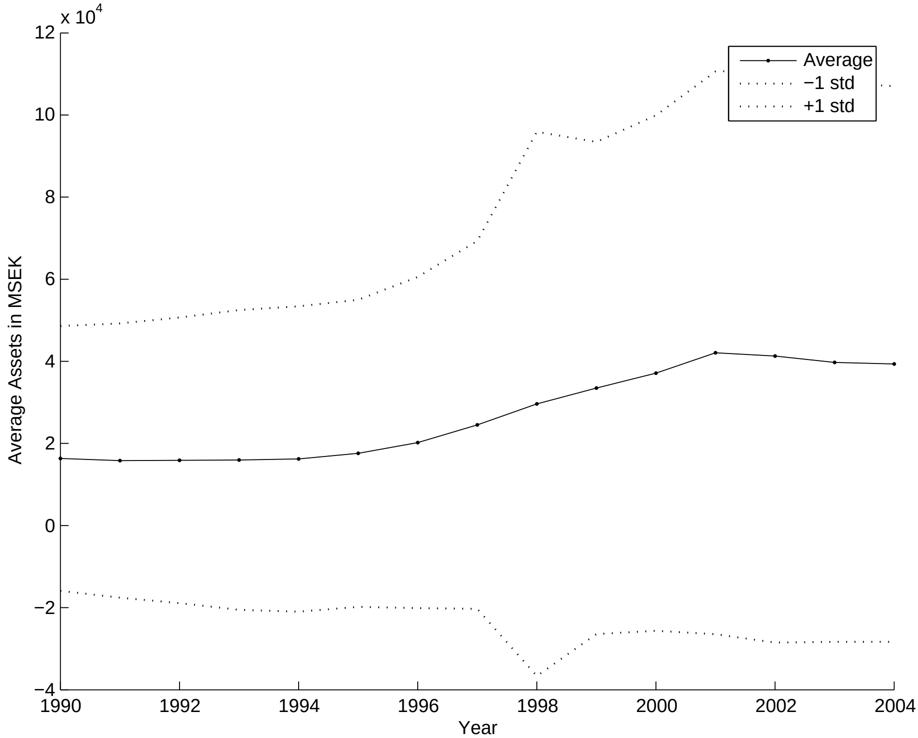
Figure 3.4 Number of firms in sample over time.



As can be seen in Figure 3.4, the number of firms increased in the beginning of the sample, only to decrease from 1995 and onwards. The start of the decline of number of firms in 1996 is driven by taxation rules, where firms listed on the A-list were given a higher wealth value than unlisted securities for wealth taxation purposes. A large number of firms chose to renounce their listing. After 2000 there were a large number of buy-outs from the exchange and no new listings, so the number of firms listed on the A-list was decreasing for a large part of the sample.

The increasing average size of the firms listed on the A-list can be seen in Figure 3.5. The firms that changed listing were often smaller firms with a strong owner or group of owners, and the firms that were bought out were also smaller than average. These two effects on their own increase the average size. Added to this; the firms have also grown in size, making the change remarkable.

Figure 3.5 Average book assets in Sample over time.



3.A.2 Tax regime

The Swedish tax system was reformed in 1990-91 and the new taxation regime was fully implemented by 1992. The idea behind the tax reform was to structure the taxation to increase economic efficiency. This increased efficiency should be achieved through smaller dead weight losses from taxation and a uniform taxation between different types of income. Hansson (2006) lists the taxation level for different types of income.

- Labor income is taxed separately from capital gains, interest income and dividends (capital gains tax).
- The personal income tax has a base level of about 30 percent and a highest marginal tax rate of 58 percent. Benefits are valued at market value for taxation purposes.
- The capital gains tax is 30 percent.
- The company tax is 28 percent of company profits.
- The value added tax is set to 25 percent and encompasses most goods and services.

The personal income tax has been changed a few times since 1992. The capital gains tax has not changed since 1992. The tax on company profit has been adjusted from 30 percent of profits down to 28 percent in 1994. Even with these minor adjustment the structure from the reform is intact. The only change in taxation that is important for the capital structure choice is the change in company tax and that tax change is only 2 percent. The results in this study can not be explained by changes in taxation.

3.B Appendix - Definitions

Some of the concepts in this paper are described here.

Debt is all outstanding debt at the end of each year. The debt measure includes long term and short term debt, provisions and accounts payable. The long term debt includes bank borrowing, issued securities, and convertible loans. The short term debt includes accrued expenses, prepaid income, accrued tax costs, and other short term items. Provisions include, amongst other items, pension liabilities.

Net Debt equals all interest bearing debt less cash and marketable securities.

Earnings is the net profit to shareholders' equity.

Operating Earnings is defined as EBIT plus financial income.[28]

Internal Finance is defined as the net operating profit less taxes, interest payments and net investment.

ROE is the return to owners' equity. The return on equity is calculated on income after interest expense and tax divided by shareholders' equity.

ROA is the return on total assets. This measure is income before interest and taxes divided by total assets.

COD is the cost of debt. The return on debt is the interest expense divided by total debt.

[28] Sales-COGS-Depreciation-Amortization+Financial Income. The financial income item is added to compensate for the use of all debt.

3.C Appendix - Joint tests of mean reversion

The time-series in the sample are fairly short, so it is likely that only joint tests for a large number of firms will be able to give any conclusive answers. I use the Wald test for testing my hypotheses and they can be viewed as many joint t-tests. To be able to do joint tests between the time series, I calculate the covariance matrix for the error terms. The time series have different length so the shorter series are filled with zeros until the series are of equal length. This operation decreases some of the expected covariance matrix elements, making it harder to reject the proposed null hypotheses. The time series dimension has a maximum of only 15 yearly data points, so the covariance matrix is estimated without any lags, according to the standard setup.[29] The sample covariance matrix is calculated as;

$$\hat{\Omega} = \frac{1}{T} \sum_{m=1}^{T} f\left(X_t, \hat{\theta}\right) f\left(X_t, \hat{\theta}\right)', \tag{3.7}$$

where X_t is the data set, $\hat{\theta}$ is the estimated sample parameters, and $f(\cdot)$ is the error from the regression.

The tests assume normality of the parameters and are Wald-tests with different null hypotheses ($g\left(\hat{\theta}, \theta_0\right)$);

$$\lambda_w = g\left(\hat{\theta}, \theta_0\right)' I\left(\hat{\theta}\right) g\left(\hat{\theta}, \theta_0\right) \xrightarrow{d} \chi^2(k), \tag{3.8}$$

where $I\left(\hat{\theta}\right)$ is the Fisher information matrix, and k is the number of elements in the null hypotheses. Under regularity conditions the information matrix equals the inverse of the covariance matrix $\left(\hat{\Omega}\right)^{-1}$. The Wald test can be performed on joint hypotheses, such as "firms in the Basic Materials industry have mean reversion". I will do the same Wald test on "all firms" and "profitability".

For the test statistic to converge in distribution (equation (3.8)) the data set has to have a large number of observations. The average number of time periods in my sample is not large, so I use pooling to mitigate this problem. This solution to the situation is not optimal, since it requires that the cross-sectional variation is limited. If the cross-sectional variation is large, the results will not be significant.

[29] This is a standard Wald test and the set-up can be found in advanced textbooks of statistics such as Hamilton (1994).

3.D Appendix - Robustness of mean reversion test

For the mean reversion estimates from Table 3.6 to be correct there has to be a large number of time periods. I do not have a large number of time periods in my sample and to mitigate this firms have been pooled before running the OLS regressions presented in Table 3.6. Another "pooling" test is constructed in this appendix. The test constructed here relies heavily on the setup of Arellano & Bond (1991), who have constructed a test for small T and large N. For the problem at hand here there is a panel data set with few time periods but with many firms. Note that this test deviates from the earlier tests in that the gamma (γ) is not determined for each company but for a set of companies jointly.

The model I wish to estimate is a first difference autoregressive model with one exogenous variable. The notation follow Arellano & Bond (1991), but the translation to equation (3.3)(p. 122) is straight-forward.

$$y_{i(t+1)} - y_t = \delta + \gamma \left[y_{it} - y_{it}^* \right] + \nu_{it} \tag{3.9}$$

where δ is an intercept, γ the coefficient of interest, and $i \in N$ is a firm index. Assuming that a random sample of N time series $(y_{it}, ..., y_{iT})$ is available. T is small and N is large. y_{it}^* is exogenous and ν_{it} has finite moments, where $E\left[\nu_{it}\right] = E\left[\nu_{it}\nu_{is}\right] = 0$ for $t \neq s$. With these assumptions, the three periods or more lagged values of y are valid instruments for the first difference of equation (3.9). The equation is valid for the adjoining time periods as well.

$$y_{it} - y_{i(t-1)} = \delta + \gamma \left[y_{i(t-1)} - y_{i(t-1)}^* \right] + \nu_{i(t-1)} \tag{3.10}$$

Taking the expected value of the difference between equation (3.9) and equation (3.10) and multiplying with the instruments $(y_{i(t-j)})$ gives the moment conditions. Define $\bar{y}_{it} = y_{it} - y_{i(t-1)}$ to follow the notation of Arellano & Bond (1991).

$$E\left[\left(\bar{y}_{it} - \bar{y}_{i(t-1)} - \gamma \left(\bar{y}_{i(t-1)} - \bar{y}_{i(t-1)}^* \right) \right) y_{i(t-j)} \right] = 0 \quad (j = 3, ..., (t-1), t = 4, ..., T) \tag{3.11}$$

The maximum number of moment conditions are (T-3)(T-2)/2 for each firm. There is one less possible instrument compared to the original Arellano and Bond test since the mean reversion test is a difference test to start with. I have an unbalanced panel, so many of the possible moment conditions disappear due to lack of data.

The results from running the test in equation (3.11) are presented in Table 3.D.1 below. In the sample the number of moment conditions is less than half of the maximum. For the calculations an inefficient weighting matrix was used, the identity matrix. This choice of weighting matrix might decrease the significance of the parameters.

Table 3.D.1. Arellano and Bond based test of Mean reversion by industry.

Industry (ICB)	Book Value Based Mean Reversion			Nr Moments.	Market Value Based Mean Reversion			Nr Moments
All Firms	-0.74	-20.7	***	4804	-1.04	-27.1	***	4481
Oil & Gas	-2.14	-4.6	***	55	-4.10	-11.9	***	55
Basic Materials	-1.08	-8.9	***	798	-1.29	-10.3	***	760
Industrials	-0.87	-17.4	***	2034	-0.72	-13.1	***	1860
Consumer Goods	-0.08	-0.6	***	447	-0.01	-0.1		427
Health Care	-0.13	-1.9	***	281	-0.01	-0.2		245
Consumer Services	-0.57	-5.8	***	283	-0.09	-1.4	***	276
Telecommunications	-0.29	-1.7	***	52	0.04	0.3		40
Utilities	-0.07	-0.3		116	0.45	2.1		101
Real Estate	-0.64	-5.2	***	357	-0.84	-6.5	***	345
Technology	-0.73	-6.9	***	381	-0.74	-10.2	***	372

The mean reversion coefficient (γ) is calculated using GMM of Hansen (1982) in an Arellano & Bond (1991) setup. The t-statistics are the robust estimator from the GMM calculations. The number of moments are the number of moment conditions used to calculate the coefficient. The coefficients were calculated with the Identity matrix for weighting. The mean reversion estimates are tested against a Dickey-Fuller distribution. Coefficients significance levels are marked with ***,**, and * for 1%, 5% and 10% levels.

The coefficients are larger (and negative) for 'All Firms' both in the book value based and the market value based sample than the estimates reported in Table 3.6. The mean reversion of the aggregate is thus larger. The market value based leverage has a coefficient estimate below -1, meaning that it converges over time, but not smoothly. Many of the coefficients in the industry sample also have larger negative estimates, implying that the OLS test of Table 3.6 might yield too low estimates of the mean reversion coefficients.

The significance of the mean reversion parameters vary in strength, but are generally high, especially considering that they are calculated from a difference of difference setting with robust standard errors.

The conclusion from the robustness test is that there is evidence for the mean reversion. The higher coefficient estimates are dented by the slightly smaller significance levels than the ones in Table 3.6. The null hypothesis of no mean reversion can be rejected for most of the tests in Table 3.D.1.

3.E Appendix - Book value based trade-off results

The results for the book value based estimates below in Table 3.E.1 are similar to the results in Table 3.5.

Table 3.E.1. Regressions for predicting debt-to-asset (book) ratio.

Proxy	Profitability		Non-Debt Tax-Shield		Growth Options		Volatility of Earnings		All Attributes	
Constant	0.61	***	0.59	***	0.58	***	0.58	***	0.69	***
Earnings/Assets	-1.04	***							-1.01	***
$\overline{op.earnings}$/Assets	-0.03	**							-0.03	
R&D/Sales			-0.59	***					-1.69	**
Depreciation/Assets			-0.93	***					-0.92	***
Market-to-Book					0.00	***			0.00	***
Market-to-Assets					-0.07	***			-0.03	***
R&D/Assets					-0.40	***			1.48	**
Stock Returns					0.01	**			0.00	*
Log of Assets							-0.01	***	-0.00	
Fixed Assets/Assets							0.07	***	-0.01	
R^2	0.24		0.05		0.27		0.01		0.47	
$\overline{R}^2$	0.23		0.05		0.27		0.01		0.47	
Nr Obs.	1037		1288		1005		1325		767	

$(D/A)_{j,t} = \alpha_j + \beta_j f_{j,t} + \varepsilon_{j,t}$

The Market-to-Book is the market value of equity divided by the book value of equity, the Market-to-Assets is the market value of equity divided by the book value of assets, and the Stock Return is the return on a share held since the preceding year. $\overline{Op.earnings}$ is the average operating earnings over three years. The coefficients are from a standard OLS regression. (The coefficients have been compared to a censored tobit regression and only differ slightly in the t-statistics.) The asset values are calculated using the book value of equity. $\overline{R}^2$ is the adjusted R^2. Observations lacking data points have been dropped. Coefficients significance levels are marked with ***, **, and * for 1%, 5% and 10% levels.

The earnings and average operating earnings are both negative in Table 3.E.1 like in Table 3.5. The tax shield argument is supported by the negative and significant coefficients on R&D/Sales and Depreciation/Assets. The growth options proxies have both negative and positive coefficients. It is unexpected that the market-to-book coefficient is positive when the market-to-assets is negative, since the only difference is the debt in the denominator. The volatility of earnings is insignificant. The significance levels of the explanatory variables are generally high and the explained variation, as measured by R^2 and $\overline{R}^2$, is in line with Hovakimian et al. (2001). The collinearity of the two R&D measures persists also for the book value based estimates. The R&D scaled by assets is dropped for the book value based prediction of optimal leverage.

The coefficient estimates are used to calculate an optimal leverage for each firm. The variables with the largest impact on the optimal leverage are the Market-to-Assets, Market-to-Book, Earnings, and Depreciation.

The industry specific coefficients are presented in Table 3.E.2 below.

Table 3.E.2. Regressions for predicting debt-to-asset (market) ratio per industry.

Proxy	Oil& Gas	Basic Mat.	Industrials	Cons. Goods	Health Care	Cons. serv.	Telecom.	Utilities	Real Estate	Tech.
Constant	0.89	0.58	0.81	0.79	0.08	0.08	0.89	1.46	0.73	0.14
Earnings/Assets	-0.58	-0.59	-1.23	-0.64	0.15	-0.98	-0.58	-2.24	-0.50	-0.23
$\overline{op.earnings}$/Assets	-0.32	0.17	-0.27	-0.07	-0.16	1.17	-0.32	-0.22	-1.66	-0.42
R&D/Sales	-0.36	0.33	-0.91	-0.62	-0.76	-0.00	-0.36	1.77	0.00	-1.09
Depreciation/Assets	-0.82	-0.16	-1.02	-0.53	3.72	0.17	-0.82	-1.49	-1.30	0.21
Market-to-Book	0.01	0.03	0.02	0.01	0.06	0.06	0.01	0.09	0.11	-0.02
Market-to-Assets	-0.46	-0.20	-0.31	-0.45	-0.13	-0.30	-0.46	-0.46	-0.82	-0.01
Stock Returns	0.00	0.05	-0.00	0.01	-0.05	-0.04	0.00	0.02	-0.00	-0.00
Log of Assets	-0.01	-0.03	-0.01	-0.00	0.02	0.06	-0.01	-0.06	0.01	0.03
Fixed Assets/Assets	-0.06	0.39	0.01	0.18	-0.32	-0.00	-0.06	-0.12	0.04	0.25
Nr Obs.	10	100	344	71	31	39	2	18	62	69

$(D/A)_{j,t} = \alpha_j + \beta_j f_{j,t} + \varepsilon_{j,t}$

The Market-to-Book is the market value of equity divided by the book value of equity, the Market-to-Assets is the market value of equity divided by the book value of assets, and the Stock Return is the return on a share held since the preceding year. The coefficients are from a standard OLS regression. (The coefficients have been compared to a censored tobit regression and only differ slightly in the t-statistics.) The asset values are calculated using the market value of equity. $\overline{Op.earnings}$ is the average operating earnings over three years. Observations lacking data points have been dropped. $\overline{R}^2$ is the adjusted R^2. Coefficients significance levels are marked with ***,**, and * for 1%, 5% and 10% levels.

The industry specific coefficients will not be discussed, since there are the same problems with these as with the over all coefficient but with the added problem of fewer observations. The number of observations reported are the firm-year observations in excess of those necessary for estimating the coefficients (i.e. degrees of freedom).

3.F Appendix - Dickey-Fuller Table

Table 3.F.1. Simulated Dickey-Fuller t-statistics.

Obs	1 percent	2 percent	5 percent	10 percent	90 percent	95 percent	98 percent	99 percent
4	-69.24	-34.57	-14.11	-7.26	-0.27	0.27	1.29	2.53
5	-13.51	-9.54	-6.04	-4.27	-0.55	-0.14	0.42	0.90
6	-8.33	-6.51	-4.92	-3.89	-0.71	-0.31	0.19	0.59
7	-6.70	-5.67	-4.47	-3.68	-0.81	-0.44	0.04	0.39
8	-6.01	-5.16	-4.22	-3.57	-0.86	-0.49	-0.05	0.25
9	-5.59	-4.92	-4.07	-3.50	-0.92	-0.55	-0.12	0.17
10	-5.27	-4.69	-3.98	-3.45	-0.96	-0.61	-0.20	0.10
11	-5.17	-4.62	-3.92	-3.40	-1.00	-0.65	-0.23	0.06
12	-5.00	-4.50	-3.86	-3.37	-1.01	-0.66	-0.25	0.04
13	-4.91	-4.47	-3.84	-3.36	-1.03	-0.69	-0.27	0.01
14	-4.80	-4.37	-3.77	-3.34	-1.05	-0.71	-0.31	-0.03
15	-4.77	-4.32	-3.74	-3.32	-1.07	-0.72	-0.33	-0.05
16	-4.62	-4.25	-3.73	-3.30	-1.08	-0.75	-0.36	-0.08
17	-4.64	-4.23	-3.72	-3.30	-1.10	-0.76	-0.37	-0.10
18	-4.58	-4.21	-3.70	-3.29	-1.10	-0.77	-0.38	-0.11
19	-4.55	-4.19	-3.67	-3.29	-1.11	-0.77	-0.38	-0.11
20	-4.48	-4.13	-3.66	-3.27	-1.13	-0.79	-0.42	-0.16
21	-4.51	-4.15	-3.65	-3.27	-1.13	-0.79	-0.40	-0.15
22	-4.44	-4.10	-3.63	-3.26	-1.13	-0.79	-0.40	-0.14
23	-4.41	-4.07	-3.62	-3.24	-1.14	-0.82	-0.45	-0.17
24	-4.35	-4.05	-3.62	-3.25	-1.14	-0.81	-0.44	-0.14
25	-4.39	-4.05	-3.60	-3.23	-1.16	-0.81	-0.44	-0.18
50	-4.19	-3.90	-3.51	-3.18	-1.20	-0.89	-0.52	-0.27
100	-4.05	-3.82	-3.46	-3.15	-1.23	-0.91	-0.54	-0.28
250	-4.00	-3.76	-3.43	-3.14	-1.23	-0.91	-0.55	-0.30
500	-3.97	-3.73	-3.40	-3.13	-1.23	-0.92	-0.55	-0.30
1000	-3.95	-3.73	-3.42	-3.13	-1.25	-0.95	-0.57	-0.30
1200	-3.97	-3.74	-3.40	-3.12	-1.24	-0.93	-0.58	-0.32

Case 4. $y_t = \alpha + \rho y_{t-1} + \delta t + \varepsilon_t$
The probabilites in the heading are the left hand tail of the distribution.

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