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Dishonest strategies when issuing debt

A risk-shifting and earnings-management analysis

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Abstract

In this thesis we have investigated if companies engage in earnings management prior to issue of debt, and if asset volatility increases after. We used three models to look for earnings management, a cross-sectional model, a decile divided model and a panel data model. The cross-sectional model struggled to provide prediction of "normal" accruals, and thus proving to not be reliable to conclude on significance. The decile divided model proved to be a better fit than the cross-sectional model. However there seemed to be a systematical error which we couldn't control for, resulting in negative Z-values. This meant that although we got promising average prediction errors, we couldn't conclude if there was a significant difference. The panel data approach was implemented to control for covariance between error terms. Both the cross-sectional and decile divided model assumed covariance to be zero. We used the cross-sectional model as the basis when building the model. Using the cross-sectional model as basis proved to be detrimental for the panel model, this is because we transferred the inability to predict "normal" accruals to the panel model. The result was insignificant results from the panel model as well. We found an increase in average volatility of 11,5 percentage points after debt issue. We also found an increase in the number of companies which had significantly higher volatility one year after issue, compared to issue year. The risk-shift analysis gave support to our hypothesis of increased volatility after debt issue. We were also unable to confirm a relation between companies engaging in earnings management prior to debt issue and subsequently increasing volatility after.

Abstrakt

I denne oppgaven har vi undersøkt om bedrifter driver med regnskaps manipulasjon før opptak av gjeld, og om volatiliteten i selskapet øker etter opptak av gjeld. Vi brukte tre modeller for å se etter regnskaps manipulasjon, en tverrsnitts modell, en desil delt modell og en paneldatamodell. Tverrsnitts modell slet med å gi gode prediksjoner om "normale" periodiseringer, og viste seg dermed å ikke være pålitelig for å konkludere med betydning. Den desilfordelte modellen viste seg å passe bedre enn tverrsnitt modellen. Det så ut til å være en systematisk feil som vi ikke klarte kontrollere for, noe som resulterte i negative Z-verdier. Dette betydde at selv om vi fikk lovende gjennomsnittlige prediksjonsfeil, kunne vi ikke konkludere om det var en betydelig forskjell. Paneldatatilnærmingen ble implementert for å kontrollere for samvariasjon mellom feilleddene. Både tverrsnitt og desilfordelt modell antok samvariasjon til å være null. Vi brukte tverrsnitts modellen som grunnlag når vi bygget modellen. Å bruke tverrsnitts modellen som basis viste seg å være et dårlig valg, dette fordi vi overførte manglende evne til å forutsi "normale" periodiseringer til panelmodellen. Resultatet ble ubetydelige resultater også fra panelmodellen. Vi fant en økning i gjennomsnittlig volatilitet på 11,5 prosentpoeng etter utsteding av gjeld. Vi fant også en økning i antall selskaper som hadde betydelig høyere volatilitet ett år etter utstedelse, sammenlignet med utstedelsesår. Risiko-skift analysen ga støtte til hypotesen om økt volatilitet etter utstedelse av gjeld. Vi klarte heller ikke å bekrefte forholdet mellom selskaper som driver med inntektsstyring før gjeldsemisjon og deretter økte volatiliteten etter.

Preface

This thesis is the finalization of our master´s degree program in Business & Administration with specialization in Financial Economics at OsloMet. We chose this topic because debt is a big part of modern finance. We were especially interested to see whether theoretical incentives translated to real life behavior. We would like to thank our supervisor Johann Reindl. Through conversations, we have gotten good guidance, and been pushed to our full potential. The work process has been demanding, but we have learned a lot, and the process has been both fun and interesting.

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Content

1 Introduction

Issuing of debt is a central part of modern economy. Practically every company has debt in some form, like credit, bonds or loans from banks. Like with many other scenarios in economy we believe that the owners of companies, through managers, have incentives to not be completely honest when issuing debt. All debt, at least in the capital markets, have yield or interest to ensure the creditors earn money on the loans, where the yield or interest consist of a risk-free rate plus a risk-premium sat by the creditors. The honest way to reduce the risk-premium would be to engage in low-risk activities, but we believe there are other dis-honest alternatives.

We believe there are two ways to ensure a low risk-premium without engaging in low-risk activities. The first is through risk-shifting. Risk-shifting is the act of engaging in low-risk activities before new debt and then start with the high-risk projects after debt with a low interest or yield is secured. The other way is through manipulations of the financial statements, called earning management. Where you through accounting tricks create a perceived safer company to reduce the yield. Reducing perceived risk is a cheap and, in some instances, an easy alternative to reduce the risk premium.

In this thesis we are going to empirically examine managers behavior before, during and after debt issue. We investigate strategies that we believe would have a positive impact for the shareholders if succeeded.

The strategies that we wish to investigate must have a theoretical reasoning of why the companies might have incentives to engage in them and be possible for us to empirically test. We found sufficient incentives in literature and ways to empirically investigate risk-shifting and earnings management.

We are going to use an event study approach with issuing of debt as time zero, and investigate two years prior and after, totaling five years. Further we are going to use a quantitative method where we want to investigate as many companies as possible to find systematic changes rather than company specific events.

1.1 Structure of thesis

This thesis is divided in 7 chapters.

Chapter 2 looks at risk-shifting and the first step will be to introduce the theoretical foundation of why we believe that managers have incentives to engage in risk-shifting behavior. In order to understand why managers can have incentives to increase risk, we will start off with theory explaining how and why companies finance themselves. This is general corporate finance literature and will be important in explaining advantages and disadvantages of risk. The next step will be to introducing literature explaining why increased risk could be positive for the equity holders and therefore why mangers have incentives to increase risk. We then look at empirical methods of calculating Risk-Shifting.

In chapter 3 we present earnings management. Chapter 3 follows the same structure as chapter 2, it starts off with a presentation of literature on earnings management. Here we present what earnings management is, and how and why we believe that managers have incentives to engage in earnings management. We then look at empirical methods of testing for earnings management.

Chapter 4 is development of hypothesis. Here we present key findings from our literature reviews, and form hypothesis based on these findings. We have created several hypotheses for both risk-shift and earnings management.

Chapter 5 is data collection, here we present our data sample and how we created our data sets. We will also present various descriptive statistics.

Chapter 6 is empirical analysis. In this chapter we present the results from several empirical test regarding both risk-shift and earnings management.

In chapter 7 we conclude on our findings. We will be addressing our results and see if they give support to our hypothesis.

2 Risk-Shifting

2.1 Literature: Capital structure

2.1.1 Static tradeoff theory

In a perfect capital market, a company's capital structure will not have an effect on the company's value (Modigliani & Miller, 1958). The argument is that increased leverage in a company will reduce the equity capital necessary to finance the company but will increase the required rate of return because of increased volatility of the equity. Further, if an investor wants to increase the systematic risk to increase the expected return, he can create the leverage himself through loaning money and invest in other assets. The effect is that a levered company is not more valuable than an unlevered company. The assumptions for the M&M theorem are no taxes, no transaction costs, no bankruptcy costs and that the company and individual investor can borrow at the same rate. The assumption of perfect capital markets is unrealistic for the actual world, but the theory is a good foundation to understand capital markets and where to look for flaws and weaknesses in the real-world markets.

(Modigliani & Miller, 1958) then loosens the assumption of no taxes and shows how introducing taxes creates a tax-shield. This means interest rates becomes a tax-deductible expense and therefore leverage does increase the companies' value. This effect is offset at some point as increased leverage is increasing the company risk. The increased risk is increasing the probability of bankruptcy, and as there are costs associated with going bankrupt the increased probability of these costs occurring is lowering the company value. Further a company in financial distress may find it harder to run the company because customers and employees may be looking for alternative companies to work and trade with. This creates an optimal point where the increased bankruptcy costs offset the additional tax-shields (Modigliani & Miller, 1958). This theory is called the static tradeoff theory.

2.1.2 Pecking order theory

After the M&M theorem were published a lot of research were done trying to find the optimal capital structure. "Since then there has developed a burgeoning theoretical literature attempting to reconcile Miller's model with balancing theory of optimal capital structure" (Bradly, Jarrel, & Kim, 1984, s. 857). Another theory trying to explain the company's capital structure is the Pecking order theory, the term was introduced in (Myers, 1984). In this theory leverage is decided from what possibilities a company have when financing themselves. The theory states that companies prefer internal financing, like retained earnings. If outside financing is required the company would issue debt first, then hybrid securities like convertible bonds and only as a last resort issue new equity (Myers, 1984). This is confirmed in (Frank & Goyal, 2009) where companies with more profits have lower leverage.

There is a lot of literature trying to empirically test the different theories and what other factors that might explain a company's leverage. It is empirical evidence supporting both the static tradeoff theory and the pecking order theory. One factor that is positively correlated to leverage is tangible assets (Murray & Vidhan, 2009). As a company have tangible asset to serve as collateral for the banks, it allows the company to take more advantage of the tax shields generated from interest rates before the bankruptcy costs arise. In our thesis when investigating the issuing of bonds, the yield is essential for the equity-holders. An increase in risk would increase the probability of bankruptcy, the increased probability of bankruptcy would then increase yield/interests on future debt. This contradicts the idea that managers have incentives to increase risk, as it should increase the present value of bankruptcy costs lowering the companies value. The M&M-theorem and the Pecking order theory argue that risk is bad for company value through bankruptcy and distress costs. The theoretical explanation of why managers can have incentives to increase risk are not found from M&M or the Pecking order theory. The incentives for risk shifting are not found from theories about company value but rather from theories about equity value. The theories do however offer a key in where to investigate for risk shift.

2.2 Literature: Risk-Shifting

A_t	Asset value at a certain time
E_t	Equity value at a certain time
σ	Volatility
μ	Continuously compounded drift
T	time
r	Continuously compounded risk-free rate
W_t	Brownian motion
Q	Dividend
B_t	Value debt at a certain time
PO_t	Payoff at a certain time
ϵ	$standard\ normal\ distribution$
Φ	cumulative standard normal distribution
D	Face-value debt (total-liabilities)

Table 1 Notation used in Risk-shift analysis

2.2.1 Merton

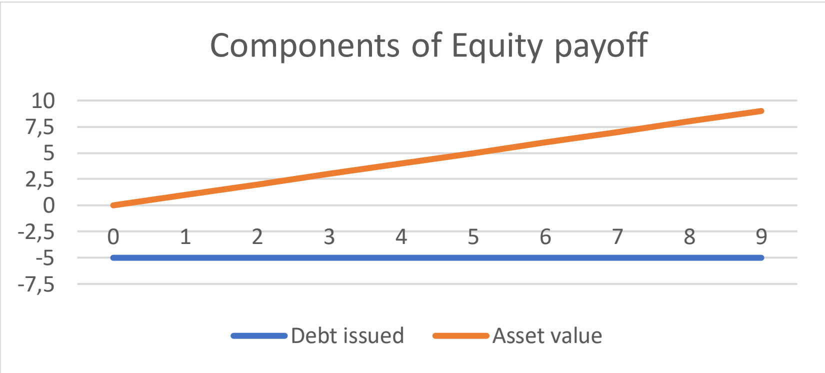
There are several ways to estimate the equity value. Like using the expected future cash flows and discount with the appropriate discount rate. Another method is valuing using multiples, where you look at similar companies and assume different ratios are the same, (P/E, P/B etc.).

In this thesis we are going to value equity as a call option. The principle is that if the asset value exceeds the value of debt at maturity, it is better for the equity holders to run the company and pay the debt. If the company is valued lower than its debt at maturity, it is better to hand over the control of the company to the creditors through declaring bankruptcy. The ability to declare bankruptcy at maturity is causing a situation where the lowest possible value for a stock is zero, the same as a long position in a call option (Merton, 1974)

$$Payoff: PO_t = Max(A_t - D, 0) \qquad (2.1)$$

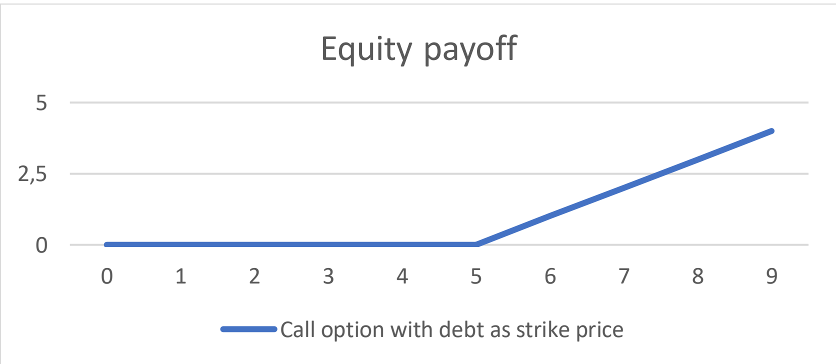
$$Value: E_t = C^{BS}(A_t, D, \sigma, r, T - t) \qquad (2.2)$$

(In all our examples debt equals to 5)



Graph 1: illustration of how equity payoff is comprised with respect to asset value. Y-axis is value and X-axis is the asset value.

The components of equity payoff (graph 1) consists of asset value and the face value of debt (-5). The ability to declare bankruptcy yields a payoff on maturity equal to being long in a call option with debt as strike price (Graph 2).



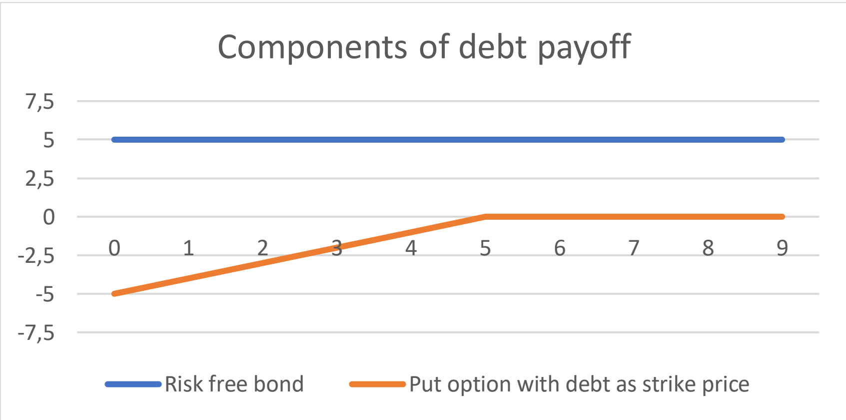
Graph 2: Graphical illustration of equation 2.1 Y-axis is equity payoff and X-axis is asset value

The equity payoff has a limited downside but a theoretical infinitive upside, shown in equation (2.1). Equation (2.2) shows that the value of equity can be estimated with the Black Scholes formula.

The situation is different for the creditors. The best possible outcome is to receive the debt in the full amount. If the company is worth more than the debt the creditors still only get the outstanding debt. However, if the company defaults and must declare bankruptcy the investors might not get back the full amount of the debt. This resembles having risk free debt but being in a short position in a put option.

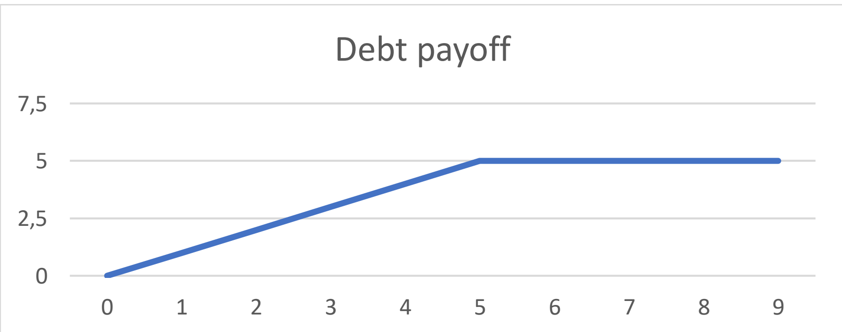
$$Payoff: PO_t = \min(D, A_t) \tag{2.3}$$

$$Value: B_t = D * e^{-r(T-t)} - P^{BS}(A_t, D, \sigma, r, T - t) \tag{2.4}$$



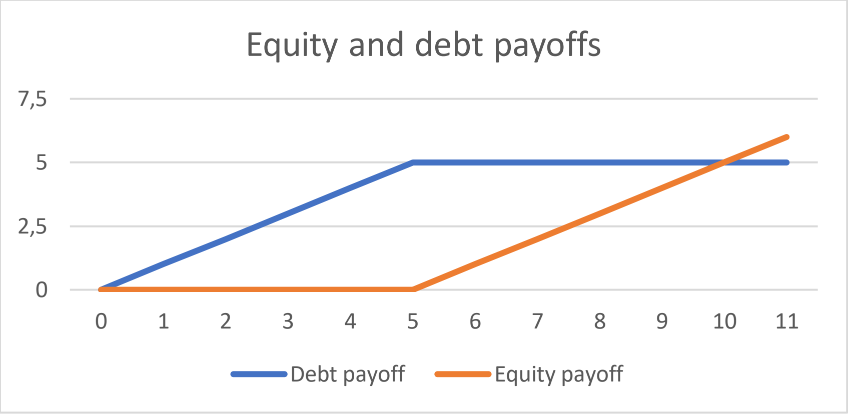
Graph 3: Illustration of how debt payoff is comprised with respect to asset value. Y-axis is value and X-axis is the asset value.

Which gives a payoff to debt holders on maturity equal to:



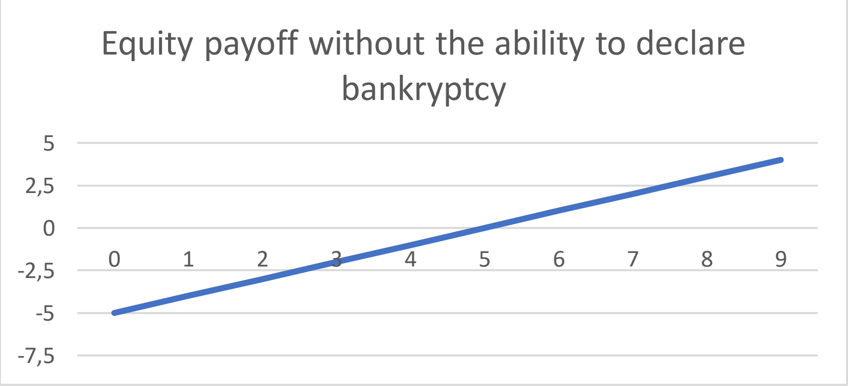
Graph 4: Graphical illustration of equation 2.3 Y-axis is debt payoff and X-axis is asset value

The payoff will be the smallest amount of the face value of debt or the value of the company, shown in equation (2.3). If the company is worth less than the debt, the equity holders declares bankruptcy and hands over the control of the company to the debtholders. The value is the debt outstanding discounted by the continuously compounded risk-free interest rate, minus the value of the put option, calculated with the principles of the Black Scholes formula (Merton, 1974).



Graph 5: X-axis is asset value and Y is payoff

This payoff is only possible because equity holders have limited liability and can declare bankruptcy on maturity of the debt. If equity holder didn't have this opportunity, debt holders would have a claim on the full amount. Equity holders on the other hand would have a payoff on maturity like this:



Graph 6: a situation where owner of companies has full liability on debt. Y-axis is payoff and x-axis are asset value

2.2.2 Assumptions of the distribution of asset value

In this thesis we will assume that company value follows a geometric Brownian motion (continuous time-stochastic process with a percentage drift). On the continuous time model the movement would be:

$$dA_t = \mu A_t d_t + \sigma A_t d\epsilon\sqrt{dt}_t \qquad (2.5)$$

(Hull, 2018, s. 335).

When A_t follow the process presented in equation (2.5) we can use Ito's lemma to derive the process followed by lnA_t. Where the expected log value is normally distributed with a mean of today's log value with a drift equal to $\left(\mu - \frac{\sigma^2}{2}\right)(T-t)$ and a variance equal to $\sigma^2(T-t)$.

$$lnA_t \sim N\left[lnA_t + \left(\mu - \frac{\sigma^2}{2}\right)(T-t),\ \sigma^2(T-t)\right] \tag{2.6}$$

(Hull, 2018, s. 337)

2.2.3 Black Scholes Merton

From tradeoff theory, increased leverage increases risk and the increased risk is causing bankruptcy costs offsetting the value of the tax shields. It appears from the leverage theories that risk is destroying value. To explain why managers can have a theoretical incentive to increase risk we will use the principles from the Black Scholes option pricing formulas and Merton presented earlier. The Black Scholes model follows the principles of asset value behavior from the log-normal property, presented in chapter (2.2.2). The formula presents how to calculate the value of a call option (C^{BS}). (Merton, 1974) suggested using the formula when estimating equity value.

Black Scholes formula:

$$E_t = C^{BS} = A_t\Phi(d_1) - D * e^{-r(T-t)} * \Phi(d_2) \tag{2.7}$$

$$d_1 = \frac{\ln\left(\frac{A_t}{D}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{(T-t)}} \tag{2.8}$$

$$d_2 = \frac{\ln\left(\frac{A_t}{D}\right) + \left(r - \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{(T-t)}} = d_1 - \sigma\sqrt{(T-t)} \tag{2.9}$$

The Black Scholes formula is calculated under several assumptions, one is that:

> “The stock price follows a random walk in continuous time with a variance rate proportional to the square of the stock price. Thus the distribution of possible stock prices at the end of any finite interval is log- normal. The variance rate of the return on the stock is constant” (Black & Scholes, 1973, s. 640).

There are several factors here that is unrealistic for the real world, interest rates are changing and volatility are not constant. Volatilities also tend to cluster together, which mean that the volatilities exhibit periods of high and low volatility, also known as ARCH-effects. “ARCH-effects: non-homogeneity of volatility together with highly significant autocorrelation in all measures of volatility despite insignificant autocorrelation in raw returns” (Lux & Marchesi, 1999, s. 677). We still find the theory sufficient in understanding why equity-holders have risk-shifting incentives.

From the Black & Scholes (1973) and Merton (1974) principles we can see how risk affects the value of debt and equity. Seeing as options are an increasing function of volatility, both the put and the call option will be worth more with increasing volatility. The total value of the company consists of both a long call and a short put position in real options. As both put and call options increase with volatility, volatility does not change the *company* value (because of one short and one long position). The increased volatility rather shifts value from the debt holders to the equity holders.

Asset value and therefore also asset volatility is not directly observable from the markets and must be estimated. A well-established method to estimate asset value is to discount future cash flows (for example EBITDA) with the required rate of return minus the growth rate of the company.

$$A_t = \frac{EBITDA_t}{r_{req.ret} - g} \tag{2.10}$$

This is however a subjective and difficult calculation, especially regarding the growth rate. We would use the volatility of the company value as a measurement of a company’s risk. The volatility would be defined as the annual standard deviation of the company value. Because of difficulties when calculating the total companies value it is better to use information from the market to estimate the implied value and volatility rather than estimating them ourselves. The calculations for total company value using EBITDA would be time consuming, highly subjective and therefore inaccurate at best. Using the available information from the markets is a better option. As the equity value, interest rates, yield and face value of debt are all observable factors, the inverted Black Scholes can be used through numerical calculation to estimate the company value and volatility. We will present our method for estimations in chapter (2.3).

2.2.4 Theory summarization

On the one hand, the theories from Pecking order and Static-Tradeoff tells us risk is bad for the total company value. On the other hand, the principles from Merton and Black-Scholes formulas tells us that risk may be positive for the expected equity value while not changing asset value. There are therefore several effects at play at once when managers decide on risk and leverage, that will have endogenous effects on each-other. It would be difficult to separate what is natural risk and what is caused by risk-shifting. The theories do however offer an understanding in what causes these incentives, and therefore is a key when investigating risk shifting.

We think there exists a theoretical optimal point where the positive effects from leverage and risk are offset from the increasing bankruptcy costs. If the management seek to maximize shareholders value, the companies should be found somewhere around this optimal point. The theories have somewhat different empirical results showing that the real world is more complex than the theories suggests. Finding evidence of risk shifting will therefore be difficult. The theories do however give some clues for where to look for risk shifting. The theories (Modigliani & Miller, 1958), (Myers, 1984), (Black & Scholes, 1973), (Merton, 1974) tells us that risk can lower the company value through bankruptcy costs, but that risk may still be positive for the equity holders through the transfer of value from debtholders. This is causing a tradeoff for the equity holders where risk affects the stock value both ways and should create an optimal point of risk. As there should exists an optimal point of risk, we should look for places in time where we believe this point changes. We believe such an event may be when a company issues debt. We will be measuring risk after issuing to see if the company risk shifts after debts is issued. This is an event study approach where the event year will be when the company issues debt.

2.2.5 Existing empirical research on Asset substitution

Risk shifting, also known as asset substitution, has been a subject of investigation for several decades. (Jensen & Meckling, 1976) found that asset substitution is a big component in the agency cost of debt. (Peters, 2006) finds evidence of asset substitution, but the results are only robust for companies that increase long-term debt. (Peters, 2006) further looks at whether leverage induces a higher risk than what may be explained through economic theories. Leverage might induce higher risk because of unknown factors that affects leverage and risk at the same time. The leverage risk relation might make it hard to know what is risk-shifting and what is caused by natural economical effects, because leverage has an endogenous effect on risk. The direction of causality (positive/negative) is also an issue when assessing whether a company engage in risk shifting when issuing debt. Agency theories and classical tradeoff models offers different argumentations for the direction of causality. Some agency theories support the notion that increased leverage might reduce risk, one reason is that it can reduce the amount of wasteful investments (Wruck, 1994). classical tradeoff models derived from Modigliani and Miller (1958, 1963) often assumes that "higher asset volatility increases expected bankruptcy cost thus decreasing optimal leverage" (Peters, 2006, s. 3). The assumption stems from the notion that asset risk is determined exogenous while leverage is determined endogenously. This means that agency theory predicts a positive causal effect, while tradeoff models building on MM theorem predicts a negative causal effect.

"The asset substitution hypothesis states that leverage creates incentives to increase company risk" (Peters, 2006, s. 1). However, the endogenous nature of leverage means that there might be other company factors that can explain the increase in company risk. "Risk shifting is more pronounced when assets have shorter maturities, when the proportion of liquid assets in the asset structure is high, and when the proportion of tangible assets is low" (Peters, 2006, s. 13). This finding is supported by (Frank & Goyal, 2009) who found a statistical significant (0,01 level) negative correlation between stock variance and total debt over market value of asset, long-term debt over market value of asset , total debt over book value of asset, and long-term debt over book value of asset.

2.3 Empirical Methodology

This chapter starts with a brief introduction to some challenges when empirically testing risk-shifting. Then we introduce our method of calculating asset volatility. This is done first with a simple Merton 1-year model, where one assumes all debt has a 1-year maturity. We then expand the model and assume that maturity is a function of a companies short- and long-term liability. The last parts are how we are testing whether companies systematically engage in risk-shifting. The first method is Levenes test which is a statistical measure, and last average volatility.

The biggest challenge when conducting the risk-shifting test is the estimation of company value. There is a qualitive versus quantitative tradeoff when conducting these tests. Doing thorough calculation would provide a better estimate for each company, but consequently it would be more time consuming and difficult to analyze several hundred companies. Especially when we can't just retrieve data from the Eikon. If we can't retrieve financial numbers, we would need to estimate them, and this would lead to additional uncertainty. An example of such a factor is time to maturity which will be discussed later.

2.3.1 Merton model 1-year maturity

As mentioned in the theory chapter under the Black-Scholes & Merton we can use the equation 2.7 and observable data from the market to calculate the asset volatility, also known as implied volatility. The method used is a rearranged Merton model and the technique is an iterated approach (explained in chapter 2.3.3). The first step is rearranging the Black Scholes formula (equation 2.7):

$$A_t = \frac{\left[E_t + De^{-r(T-t)}\Phi(d_2)\right]}{\Phi(d_1)} \qquad (2.11)$$

(Löffler & Posch, 2007) presents a model using equation (2.11), under the assumptions of a 1-year maturity where there are no dividend or interest payments.

2.3.2 Merton model with a T-years to maturity

(Löffler & Posch, 2007, s. 39) presents a Merton model that uses a T-time to maturity. The advantage of using this model is that it captures a change in maturity when the companies are issuing debt. The model calculates equity as a function of three options. The one-year model assumed no interest or dividend payouts, but these assumptions would be unrealistic over several years. As the dividend and interest are paid before maturity, they have priority. This resembles a call-option with strike at zero, but the payoff is split between interest and dividend. The second option is a short put with a strike price at total dividend and interest payments. If the asset covers the interest and dividend but not the debt at maturity, the rest of the company value would be transferred to the creditors. The last option is long call with a strike equal to dividend, interest and liability combined. The equity-holders receive the asset value after debt is paid. We rearranged the equity formula at (Löffler & Posch, 2007, s. 42) with respect on asset value:

$$A_t = \frac{E_t + (D+Q+I)e^{-r(T-t)}\Phi(d_2) - Qe^{-r(T-t)}\Phi(k_2)}{\Phi(d_1) + \frac{Q}{Q+I}\left(1-\Phi(k_1)\right)} \tag{2.12}$$

The $d_1$and d_2 needs some adjustments from the original Black-Scholes Formula and two more components are added k_1 and k_2:

$$d_1 = \frac{\ln\left(\frac{A_t}{D+Q+I}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{(T-t)}} \tag{2.13}$$

$$d_2 = d_1 - \sigma\sqrt{(T-t)} \tag{2.14}$$

$$k_1 = \frac{\ln\left(\frac{A_t}{Q+I}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{(T-t)}} \tag{2.15}$$

$$k_2 = k_1 - \sigma\sqrt{(T-t)} \tag{2.16}$$

New variables are Q and I, where Q represents the accrued dividend payments and I accrued interest payments happening from day $t+1$ and all the way to T. (Löffler & Posch, 2007) Calculated Q with actual dividend at time zero and then used a dividend growth rate to calculate future dividend payouts. When calculating I, the coupon rate was assumed to be 4% and that the debt was growing with an annual growth rate. We used a different approach, using historical dividend and interest payouts to calculate the Q and I values. Where we use each day's individual time to maturities and sum up the dividend- and interest- payments from that specific day and to maturity.

As $T-t$ are no longer assumed to be one year we need to estimate $T-t$:

$$(T-t) = \frac{[0{,}5 * CL + 10 * (D - CL)]}{D} \tag{2.17}$$

The assumptions are that current liabilities (CL) have an average maturity of half a year and that total liabilities (D) has a maturity of ten years. When issuing bonds total liabilities should be increasing causing $(T - t)$ to increase, and therefore capture changes in maturity. The approach is otherwise similar to the 1-year Merton model and we use the iterated approach at the T-year model.

2.3.3 The iterated approach

(Löffler & Posch, 2007) has provided a way to calculate asset value, however there is a problem. We have one equation and two unknown variables, A_t and σ which also are functions of each other, meaning that when one changes the other changes as well. The solution to tackle this problem is to start off with an asset value(A_t) derived from market value of equity plus book value of liabilities. Then calculate volatility (σ) based on this initial asset value. The calculated volatility is then used to calculate a new set of asset values. The new asset value is then used to calculate a new volatility. This procedure continues until the difference between the new and old asset value is insignificant. The deviation can be calculated as the sum of squared differences between the new and old A_{t-n}. In the end we will be left with a company value A_t and a volatility from the data (Löffler & Posch, 2007).

The procedure is done simultaneous for N number of observations back in time from the moment you want to estimate. In our estimate we use daily data from one year to estimate annual volatility which means N equal to 260.

2.3.4 Measuring difference in volatility- Levenes test

After we have calculated the volatility for all companies each year of the event study, we`ll need a way to test whether there is a statistically significant changes in volatilities before and after debt issue. Brown and Forsythe (1974) presents several ways to conduct a significance test between two variances/standard deviations. There is the F-stat technique, Levenes test, Barletts test and then they present their own test, called Brown-Forsythe test. (Brown & Forsythe, 1974) argue that the F-stat and Barletts test are sensitive to the underlying distribution being close to a Gaussian distribution. Further they argue that the Levenes were inaccurate when the underlying populations had a skew. Their own tests are using a trimmed mean or a median as an estimate of central location. From the assumptions of the Log-normal model the log return from stocks are supposed to be normally distributed, and therefore the mean would be a sufficient estimation of the central value used. The chosen statistics to test the difference between the different years will be the Levenes test.

$$W = \frac{(N-k)}{(k-1)} * \frac{\sum_{i=1}^{k} N_i (Z_i - Z_{...})^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} (Z_{ij} - Z_i)^2} \tag{2.18}$$

Where:

$$Z_{ij} = Y_{ij} - \overline{Y_i} \tag{2.19}$$

$$Z_i = \frac{1}{N_i} * \sum_{j=1}^{N_i} Z_{ij} \tag{2.20}$$

$$Z_{...} = \frac{1}{N} * \sum_{i=1}^{k} \sum_{j=1}^{N_i} Z_{ij} \tag{2.21}$$

(Brown & Forsythe, 1974).

The H_o of this test is that the variances are equal. Meaning a p-value below our significance level would indicate that there is not an accidently difference in the sample means. There may be many reasons why the volatility is different, and a significant difference in a single company would not be evidence of an active risk shifting strategy. Finding a significant difference in a lot of companies however could indicate a risk shifting strategy from managers.

2.3.5 Average volatility

The following equation gives us the average volatility each event year:

${SD_t}^2$	Variance for company t
n	Number of companies

Table 2 Average volatility notations

$$SD_{Average} = \sqrt{\frac{{SD_1}^2 + {SD_2}^2 + \dots + {SD_n}^2}{n}} \tag{2.22}$$

Comparing the two tests

The two tests have advantages and disadvantages. Levenes test tells us if a company has a significant different volatility in different years but can't be used on several companies at once. The average volatility calculation has weak statistically power but can be used to calculate the average volatilities for all companies the different years.

3 Earnings-management

3.1 Literature: Earnings management

There are two bases of accounting, cash basis and accrual basis. The difference is when a company recognizes income and expenses. Under the cash basis of accounting a company record their income and expenses when cash changes hands i.e. a payment has been made (Gnanarajah, 2014). The Financial Accounting Standards Board (FASB) mentions accrual accounting in various reports. In their Statement of Financial Accounting Concepts No. 6 they describe it as:

> "Accrual accounting uses accrual, deferral, and allocation procedures whose goal is to relate revenues, expenses, gains, and losses to periods to reflect an entity's performance during a period instead of merely listing its cash receipts and outlays. Thus, recognition of revenues, expenses, gains, and losses and the related increments or decrements in assets and liabilities—including matching of costs and revenues, allocation, and amortization—is the essence of using accrual accounting to measure performance of entities" (FASB, 1985, Paragraph 145)

Accrual accounting has several principles, such as the matching principle, which states that expenses should be recognized in the same period as the revenue. When a company follows the principles of accrual accounting, it can help investors to evaluate a company's performance in a certain period (Dechow & Skinner, 2000). Often these calculations are objective and straight forward, but other times they are harder to predict and more sensitive to subjective opinions. An example are the costs regarding customers not paying, or bad debt (Bragg, 2019). This is costs that must be estimated as the loss has not happened yet and is therefore more subjective. We therefor find accruals a good place to look for potential earnings management, as there is room for subjective calculations.

Both generally accepted accounting principles (GAAP) and International Financial Reporting Standards (IFRS) require that the financial statements be prepared on the accrual basis of accounting with the exception of the cash flow statement (Ernst & Young, 2019). GAAP and IFRS both introduce subjectivity and flexibility to recognition of financial accounts, which could be called earnings management. By this definition earnings management could be used to increase the informativeness of financial statements, however if there is misalignment between management and stakeholders this could lead to management manage earnings opportunistically (Subramanyam, 1996).

There are several definitions of earnings management in the literature. Munter (1991, P.32) define earnings management as: "(earnings management) occur when companies exploit and intentionally misinterpret the accounting standards to achieve the desired earnings result". Healy & Wahlen (1999, P.368) defines it as "Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting numbers". We are going to define earnings management broadly as "actions taken by a company to alter financial reports to deceive stakeholders for personal gain". Seeing as we are looking at earnings management surrounding bond issues, the main deceived stakeholder is creditors.

(Diri, 2018) investigates earnings management motives, based on bound rationality theory, information asymmetry theory and contracting theory the book derives three main categories of earnings management motives from these theories.

Capital market motives, comes from bound rationality theory. Defined as "factors that drive earnings management through their impact on the company's stock price" (Diri, 2018, s. 76). In addition to manage earnings to improve stock prices capital market motives provide reasoning to manage earnings when a company issue equity (both initial public offering and seasoned equity offering), when a company is involved in a merger or acquisitions and in the case of management buyouts.

External motives stem from information asymmetry theory. A group of factors that the company cannot control which can give incentives to engage in earnings management activities. Factors such as regulations, accounting standards, tax considerations and country-specific policies all play a vital role in how a company run, and thus creates different incentives to whether or not a company should engage in earnings management.

The last category of motives for earnings management is contracting motives. These are incentives created by a contractual agreement. For example, a management compensation agreement can give managers incentives to engage in earnings management to fulfill his obligation and thus be eligible to receive his compensation. It is in this category we find the motive for earnings management when taking on debt. We found that our intuition on earnings management in relevance to debt is in accordance with the literature. Mainly that equity holders want as cheap debt as possible to increase their share of the future cash flows. One way to increase their share of future cashflows is to manage earnings, to make the company appear safer and/or more profitable. Being viewed as safer is likely to decrease interest rates when borrowing money, and thus creating an incentive to manage earnings.

Although there are an abundance of theoretical reasoning and motives to explain why companies or managers engage in earnings management, there seems to be little and weak results in empirical research on earnings management and company characteristics.

In addition to not having hard evidence of the relation between different company characteristics and earnings management, empirical research has provided opposing results. Especially company size and earnings management yields different results. When looking at literature it becomes evident why empirical research struggles to conclude on company size. Both small and big companies have incentives to engage in earnings management, and by the lack of evidence it can seem like these incentives are equally strong. Small companies might have incentives to engage in earnings management because they have less predictable operations and are also to a lesser extent diversified. Meanwhile, larger companies have more stakeholders and thus more issues with agency costs (Diri, 2018).

3.2 Literature: Accruals

3.2.1 Total accruals

Total accruals are not directly observable from any financial statement, this means we have to calculate them. There are presented several ways to calculate total accruals in the literature, and they have different strengths and weaknesses. Accrual models are either “balance sheet” methods or “cash-flow” methods. An example of a balance sheet approach is found in (Sloan, 1996). The idea is that the differences in the different posts should equate to the total accruals for a specific year.

$$Accruals = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep \tag{3.1}$$

ΔCA	Change in current assets
$\Delta Cash$	Change in cash/cash equivalents
ΔCL	Change in current liabilities

ΔSTD	Change in debt included in current liabilities
ΔTP	Change in income taxes payable
Dep	Depreciation and amortization expense

Table 3 (Sloan, 1996, s. 293)

An example of a cash-flow method of calculating total accruals can be found in (Hribar & Collins, 2001)

$$TA_t = EBXI_t - CFO_t \quad (3.2)$$

TA_t	Total accruals
$EBXI_t$	Earnings before extraordinary items
CFO_t	Cash flow from operations

Table 4 (Hribar & Collins, 2001, s. 109)

The balance sheet method has come under some scrutiny in the literature. The main criticism is based on the lack of correcting for the effect of non-operating events, such as mergers & acquisitions or discontinued operations. This effect could have a severe effect on the results if potential financial decisions that affect the balance sheet are correlated with the event date in a study, causing the balance sheet accruals to be biased. (Hribar & Collins, 2001).

In the late 1980s SFAS No. 95 was introduced, it changed what was required to include in the cash flow statement. These changes made it possible to calculate accruals from the cash flow statement (Sloan, 1996). Because it was introduced in the late 80s the earlier empirical analysis had no choice but to use the balance sheet method. This was the main reason why (Sloan, 1996) used the balance sheet approach to calculate accruals.

We believe that it is likely that non-operating events coincide with issuing debt, for example a company might issue debt in order to finance an acquisition. Therefore, we chose to use the cash flow method introduced in (Hribar & Collins, 2001), rather than a balance sheet method. This will result in limited data before 1990 (discussed further in the sample selection section), but we believe this is better than having biased estimates.

3.2.2 Change in accruals

There are a lot of articles investigating earnings management. (DeFond & Jiambalvo, 1992) looks at debt covenant violation and manipulation of accruals, (Dechow, Sloan, & Sweeney, 1995) evaluates different accrual-based models for detecting earnings management, (Pustylnick, 2011) uses an algorithm based on Altman Z-score to detect earnings management, (Sloan, 1996) looks at whether stock prices reflect accrual information or not and (Jones, 1991) investigates earnings management during import relief investigation. The methodology presented in (Jones, 1991) has been our foundation to empirically testing earnings management from change in accruals.

In order to calculate earnings-management we are going to look at the changes in accruals in different years. The idea is that we should be able to calculate the total accruals, then differentiate them into discretionary and non-discretionary accruals. The method is presented in Jennifer Jones' article from 1991. She calculates the total accruals and then creates a prediction model to calculate the predicted accruals, using a time-series regression for each individual company. The next step is to see if the calculated accruals in the different years deviate from the prediction model. The assumption is that the non-discretional accruals should be possible to predict from a model taking different factors into account that should affect the accruals. The rest is the discretionary accruals and could be used as a measure of earnings management.

TA_{it}	Total accruals in year t for company i
ΔREV_{it}	Revenues in year t less revenues in year t-1 for company i
PPE_{it}	Gross property, plant and equipment in year t for company i
A_{it-1}	Total assets in year t for company i
ϵ_{it}	Error term in year t for company i
i	1,……,N company index
t	1,….,T , year index

Table 5: (Jones, 1991, s. 211)

The prediction model *(Jones, 1991, s. 211)*:

$$\frac{TA_{it}}{A_{it-1}} = \alpha_i \left(\frac{1}{A_{it-1}}\right) + \beta_{1i} \left(\frac{\Delta REV_{it}}{A_{it-1}}\right) + \beta_{2i} \left(\frac{PPE_{it}}{A_{it-1}}\right) + \epsilon_{it} \tag{3.3}$$

The OLS assumptions following (Patell, 1976):

$$E(\epsilon_{it}) = 0 \tag{3.4}$$

$$cov(\epsilon_{it}, \epsilon_{it}) = \begin{cases} 0, & it \neq it \\ \sigma_{it}^2, & it = it \end{cases} \tag{3.5}$$

$$E(\epsilon_{it} | Xvariables) = 0 \tag{3.6}$$

3.2.3 Variables

She writes reasoning behind the different variables using arguments from the original accrual calculation that are used to control for economic circumstances. The variable argumentation is from (Jones, 1991, p. 211-212).

Revenue:

Total accruals are dependent on economic circumstances and revenue is included to account for the effect changes in sales will have on accruals. It is expected that the non-discretionary accruals follow the revenue and should therefore be controlled for. Revenue could be an account affected by earnings management and is therefore not entirely exogenous.

Property plant equipment:

Is included to control for the total accruals caused by depreciation expense. It is included in the expectation model rather than the total accrual calculation because depreciation is included in the total accrual calculation. In our model depreciation is included in earnings before extraordinary items (EBIX). Meaning that EBIX would be reduced with depreciation expenses.

Lagged assets:

Jones (1991) argues that there are big correlations between the error term and lagged assets.

> "All variables in the accruals expectations model are scaled by lagged assets to reduce heteroscedasticity. As described in Kmenta [1986], a weighted least squares approach

to estimating a regression equation with a heteroscedastic disturbance term (i.e., the unscaled regression equation) can be obtained by dividing both sides of the regression equation by an estimate of the variance of the disturbance term (i.e., resulting in a scaled regression equation). In this case, lagged assets (Ai,-1) are assumed to be positively associated with the variance of the disturbance term" (Jones, 1991, p. 212).

3.3 Empirical Methodology

3.3.1 Calculating the discretionary accruals

We follow the principles presented in (Jones, 1991) to measure earnings management. The theory is that using the correct variables the prediction model should capture the non-discretionary accruals and that we should be left with the discretionary accruals. In other words, the prediction error after the prediction is the discretionary accruals. The formula for the prediction error is:

$$u_{it} = \left(\frac{TA_{it}}{A_{it-1}}\right) - \left[\alpha_i\left(\frac{1}{A_{it-1}}\right) + \beta_{1i}\left(\frac{\Delta REV_{it}}{A_{it-1}}\right) + \beta_{2i}\left(\frac{PPE_{it}}{A_{it-1}}\right)\right] \qquad (3.7)$$

The estimators (α, β_1, β_2) are found using OLS (ordinary least squared) from equation (3.3). The scaling using the last year assets reduces heteroskedasticity. An assumption is that the relationship between the non- discretionary and the discretionary accruals are stationary (Jones, 1991, s. 212).

Jones (1991) follows up by creating a standardized prediction error:

$$V_{it} = \frac{u_{it}}{\widehat{\sigma}(u_{it})} \qquad (3.8)$$

The prediction errors are represented with u_{it}, and are divided with the standard deviation of the prediction error (SDPE). The calculations for the SDPE are as follows:

$$\widehat{\sigma}(u_{it}) = \sqrt{s_e^2 + s_e^2 X_0'(X'X)^{-1}X_0'} \qquad (3.9)$$

X_0 represents the matrix of the x-values from the out of sample companies implemented in the model from the company we want to investigate, and X the matrix of the x-values in the regression. s_e^2 is the standard error of the regression. The reason we are using this model is that using the standard error from the regressions do not consider an error created if the x-values from the company we are going to predict have large deviations from the mean x-values in the regression. This model gives us a lower prediction error if the X_0-values are closer to the mean x-values used in the regressions, and bigger errors if the values are far from the mean. The prediction error will also be lower the more observations we have (Geyer, 2009, s. 20). Combining equation (3.7) and (3.9) gives:

$$V_{it} = \frac{u_{it}}{\sqrt{s_e^2 + s_e^2 X_0 (X'X)^{-1} X_0'}} \tag{3.10}$$

There will be one standardized prediction error for each company for each period. The degrees of freedom for the Standardized prediction errors are calculated as, n-(k+1) (Wooldridge, 2014, s. 174). Where n equals number of observations used to predict, and k equals the number of regressors. In Jones regressions this will equal to T_i-3. The standardized prediction errors are distributed with T_i-3 degrees of freedom under the following assumptions from (Patell, 1976):

$$E(u_{it}) = 0 \tag{3.11}$$

$$cov(u_{it}, u_{it}) = \begin{cases} o & , \quad it \neq it \\ \widehat{\sigma}(u_{it})^2 & , \quad it = it \end{cases} \tag{3.12}$$

$$E(u_{it} | Xvariables) = 0 \tag{3.13}$$

The V_{it} are assumed to be; “independent random variables with known expected value and (perhaps unequal) variances, and in accordance with the Lindeberg Central Limit Theorem, a normalized sum can be formed” (Patell, 1976, s. 257)

$$Z_{Vt} = \frac{\sum_{i=1}^{N} V_{it}}{\sqrt{[\sum_{i=1}^{N} (T_i - 3)/(T_i - 5)]}} \tag{3.14}$$

In (Jones, 1991) an assumption for the calculations are no correlation between the prediction errors. She calculates using a time-series regression which means that the regressors are company specific and therefore only one issue for each regression per year. As there are individual time-series regressions for each company she gets standard deviation of the prediction errors that do not have covariances between them. This allows her to add them up without taking covariances into account.

Jones (1991) is investigating earnings management in context of companies that would benefit from import relief. The idea is that companies that may be protected from import relief have incentives to appear weaker than they actually are, and therefore attempt to reduce earnings through earnings management. She uses an event study, with the investigation period as the event. She tests if the prediction errors in the event year are significantly negative as the companies have incentives to reduce the accruals to appear more fragile to competition than they are. She therefore uses a one-sided t-stat to conclude if her prediction errors are significant negative (Jones, 1991, s. 214). In accordance with (Patell, 1976, s. 257) we will use a one-sided T-stat to look for significantly positive Z-values. Our H_0: $Z = 0$, and our H_A: $Z > 0$.

A problem with Jones' method is that we need a lot of observations for each company to make the predictions. This problem is especially for companies with limited data before debt issue which is going to be our "year zero" in this event study. A way to tackle this problem is presented in (DeFond & Jiambalvo, 1992). The idea is to use industries rather than company-specific data to estimate the coefficients. Jones' model is a time series prediction, but this new idea is called a cross-sectional Jones model. We use OLS as before to get industry and year specific coefficients to do the predictions. The specifications in the equations change a little bit, but the principles stay the same.

Calculating the prediction errors:

$$u_{ijt} = \left(\frac{TA_{ijt}}{A_{ijt-1}}\right) - \left[\alpha_{jt}\left(\frac{1}{A_{ijt-1}}\right) + \beta_{1jt}\left(\frac{\Delta REV_{ijt}}{A_{ijt-1}}\right) + \beta_{2jt}\left(\frac{PPE_{ijt}}{A_{ijt-1}}\right)\right] \qquad (3.15)$$

The j represents the specific industry. Each coefficient is therefor for one industry in one year (DeFond & Jiambalvo, 1992, s. 166).

The Z_{Vt} statistic is calculated as before, but instead of using number of observations for each company the number of companies in an industry during a specific year is used:

$$Z_{Vt} = \frac{\sum_{i=1}^{N} V_{it}}{\sqrt{\left[\sum_{i=1}^{J} (I_{ji} - 3)/(I_{ji} - 5)\right]}} \tag{3.16}$$

(DeFond & Jiambalvo, 1992, s. 168)

To conduct the tests using Jones's technique we need to keep the assumption of zero correlation or covariance between the industries and years. The prediction errors will be calculated using the $(X'X)^{-1}$ matrix for each individual regression and will therefore not include covariances between the industry-years. Further the V_{it} values are added without considering the covariance that might exist between the prediction error-terms. Because there may be covariance between the SDPE from the same regressions we are going to relax this assumption and calculate them where we do add up the covariance. (the method will be presented in the Panel-data chapter (6.4).

4 Development of the hypothesis

4.1 Main Hypothesis

We believe there are empirical and logical indications that there are incentives for both risk-shifting and earnings management. From the theoretical foundations we create one main hypothesis and sub hypothesizes for each topic.

Main hypothesis: Managers engage in dis-hones strategies when issuing debt.

4.2 Hypothesis 1, Risk shifting incentives

From the Black Scholes formulas and Merton`s theories equity can be valued as a call option. A call option is a function positively correlated with the underlying risk. In the static tradeoff theory risk is negative for company value, and there are therefore two opposing forces at work. The tradeoff theory states that risk from leverage will cause bankruptcy costs which will reduce the values from the tax-shields.

The argument that incentives to increase risk *after* the issuing of debt therefore arises from two key points from the presented theories. The first point we find in the static tradeoff theory (Modigliani & Miller, 1958), from the assumptions of perfect capital markets everybody can loan money at the risk-free rate. As we know this is not the case in the real world. Companies interest or yield is largely dependent on the risk premium required from the market. Therefore, the managers and shareholders have incentives to keep the risk low before a debt issue in order to get as low yield as possible on the loan. When an interest is locked in there is suddenly a reduced consequence of bankruptcy costs with increased risk, and if company are not going to issue debt again, the bankruptcy cost goes away.

The second point is from (Black & Scholes, 1973). Unless the issuing of new debt is just replacement of old debt, new debt changes the strike price of the perceived call. If the debt is a replacement the only thing changing will be the time to maturity. If the issuing of debt is restructuring of leverage the asset value stays the same but there will be a larger portion of the asset that is debt and thus the strike price becomes relatively closer, seen from the fraction $\frac{A_t}{D}$ in equations (2.8) and (2.9). If the bond does not replace old debt and the company keep the equity both the company value and the debt will increase, but the strike will become relatively closer to the company value. This happens because the company value must be bigger than debt. Issuing debt will cause the company value and debt to increase in absolute terms, but as the company value is bigger the difference will be relatively smaller, $\frac{A_t + New\ debt}{D + New\ debt}$. The closer the company value is to the strike price the larger the incentives to increasing risk. When close to the strike-price, the equity-holders have little to lose on increasing the risk but have an unlimited upside, because of the principles from the graphs in chapter (2.2.1). Thus, the closer the asset value is to strike-price, the higher the incentives to increase the risk. Therefore, in most cases issuing debt will get you closer to the strike price and therefore cause a higher incentive to increase risk.

Hypothesis 1.1: We will see an increase in risk after issuing debt.

Earlier we discussed the incentives changing when issuing debt, both from the principles of bankruptcy costs and from (Black & Scholes, 1973). How these incentives changes are different from company to company. A company might issue bonds regularly. In this scenario the bankruptcy cost would not decline severely as the next bond issue would not be far away. Increased risk would increase future yield. From (Black & Scholes, 1973) the leverage would with regularly bond issuing be stable over time, and therefore reduce the change in incentive from increased leverage.

Hypothesis 1.2: A higher percentage of companies that has issued only one bond will engage in risk-shifting, than companies with several bond issues.

Through (Black & Scholes, 1973) and (Merton, 1974) we found that companies with higher leverage have more incentives to engage in risk-shifting. If leverage is only increased a little bit, the incentives would be small. We calculate the leverage ratio as $\frac{Market\ value\ of\ equity}{book\ value\ of\ total\ debt}$ in accordance with (Altman, 1968).

Hypothesis 1.3: we will see a higher degree of risk shift from companies with higher leverage ratio in year zero.

4.3 Hypothesis 2, Earnings management

From (Diri, 2018) and the capital structures theories we believe that there are logical and economic reasons for dishonest managers to engage in earnings management in relevance to debt issue. In contrast from the risk shifting incentives, managers have incentives to engage in earnings management up until debt issue in order to appear a nice and sound company for creditors. We will therefore look for earnings management primarily in year zero.

Hypothesis 2.1: There is a significant increase in our statistical measure of earnings management when issuing debt

As with risk shifting there are not as much incentives to engage in earnings-management if a company issue bonds sequentially. The reason why is that earnings-management requires saving up accruals in some way through moving costs and earnings in a desired direction, but the total sum is still the same over time. Because of this principle it is not possible to push the earnings higher than expected over a longer period. Therefore, higher earnings from earnings management would cause lower earnings a different year. There may be different incentives in the different years, but it would be harder to detect systematically over multiple companies. Another point is that companies that sequentially issue bonds may be engaging in income smoothing. In our dataset such a strategy would be hard to detect as the earnings management would be higher some issue years and lower in others, creating an average prediction error close to the expected levels. These two points led us to the two sub-hypotheses regarding earnings management.

Hypothesis 2.2: We will detect higher levels of earnings management in companies that only issue bonds once or few times.

Hypothesis 2.3: We will detect higher levels of earnings management when investigating the relatively biggest issue.

4.4 Hypothesis 3, joint hypothesis

The risk measured in hypothesis 1 will be the perceived market risk or implied volatility. The measurement does not however say anything about why this potential shift occur. If the market is using the company's financial statements they could be deceived by the managers. A potential shift in the company risk may be caused by the managers fixing the financial statements rather than a change in risk from the underlying operations. Changing the underlying operations could be difficult and more time consuming than fixing the financial statements. This led us to create a joint hypothesis of risk-shifting and earnings management.

Hypothesis 3.1 Firms that engage in earnings management prior to issue of debt, will have an increased volatility after issue.

4.5 Discussions

There are several potential questions arising from the two hypothesis and the potential results we will get. The different potential outcomes are no risk shift and no earnings management, risk shift but no earnings management, no risk shift but earnings management, risk-shifting and earnings management. Depending on what the results are there may be several questions. Do the creditors discover potential earnings management and does the market? Do the creditors discover risk shift, and does the market?

Our study will mostly be an empirical study and not discuss the underlying effects too closely. We do hope that by including both the hypothesizes the empirical results will cast a light at the effects at play.

5 Sample collection

5.1 General data

Our sample is restricted to companies and bonds within the Thomson Reuters Eikon database. Thomson Reuters Eikon does not provide an easy way to retrieve equity instrument data from a bond instrument identifier or retrieve bond instrument data from equity instrument identifiers. Therefor we had to make two databases and link them up manually. The equity database consists of 9 499 equities from the US market, in US Dollar, which is formed in 2013 and before. This does not exclude companies that were delisted before 2013 i.e a company that was active from 1980-2008 would still be part of our data sample. In addition, all companies are RIC linked, and there are only common shares i.e no hybrid equities such as preferred shares (if a company has both common and hybrids, we will only get the common stock).

We removed financial and financial service companies because "(a) their financial reporting environments differ from those of industrial companies and (b) they have fundamentally different accrual processes that are not likely to be captured well by our expectations models of normal accrual activity." (Peasnell, Pope, & Young, 2000, s. 318).

The bond database comprises of corporate bonds and notes prior to 2020 in the US market and US Dollar. Excluding financial and financial service companies yields 11 413 corporate bonds. After matching bonds with issuing companies, we were left with 5272 bonds from 965 unique companies. Description of steps to match bonds and companies in appendix 1.

5.2 Risk-Shift data

The risk-shift analysis is done based on the companies that have issued bonds, and the date of bond issue is used to determine year 0 in the event study. A problem of determining year zero arise when a company issues more than one bond. The problem is to determine when the company has the biggest incentive to engage in risk shifting behavior. We believe that the bigger the bond size relative to company size, the larger the company's incentive to engage in risk shifting behavior.

Our approach to decide year zero in the event period was to sum up each bond for a given year from each company, and then assume that the year which the company issued the highest amount is the year when they have the biggest incentive. We also wanted to correct for the size of the company when the bond was issued, because we believe there is a bigger incentive when the bond is larger relative to company size. We divided the sum of issued bonds for a given year on lagged total assets. Lagged assets are used to get a measurement of company size which is independent of the bonds that has been issued for the given year.

Since our event period is two years before and after issue, we had to remove bonds issued in 2018 and 2019 due to lack of financial data in years 2020 and 2021. This dropped the number of companies from 965 to 841.This number then dropped to 290 companies in Merton T-year model, because we decided to use historical data, rather than estimating dividends and interest payments.

We download total liabilities per quarter (WC03351A), current liabilities per quarter (WC03101A), market value (MV), dividend (WC04551A), interest payments (WC01251A), and one-year US T-bill (FRTCM1Y) from Datastream. Full explanation of all variables in appendix 3.

5.3 Earning management data

The equity database with 9 499 companies is the basis for our cross-sectional regression. We have decided to use Fama-French 30 industry classification to identify which industry each company belongs to. The number of different industries needed to be large enough so the companies in each industry are relatively similar, however to many industries would lead to too few observations in industry-years. 30 industries are somewhat of an arbitrary choice, but we believe it provides a good compromise.

If the companies which we are investigating are part of the regressions, our cross-sectional analysis could suffer from bias. This bias would stem from the fact that we look at "normal" changes in industry averages. If the companies which has issued bonds are part of determining what "normal" changes are, then our regression could predict higher/lower "normal" changes. The number of companies within each industry-year varies, and thus the severity of the bias would differ from industry to industry. We decided to run the regression without these companies for each industry and year. However, a weakness with excluding these companies from all the regressions, is that there could be a systematic difference in how the different factors affect the companies. An example is how the model adjust for heteroskedasticity by dividing by lagged assets. Like the constant in the model ($\frac{1}{A_{it-1}}$) assumes a proportionally constant relation with the company size when there could be a non-constant connection. This could cause a systematic over or under estimation of non-discretionary accruals. To reduce this weakness, we excluded the companies only in the event period (years -2, -1, 0, 1 and 2).

In our dataset some industry-years have several hundred observations, we also have industries with a small number of observations. The smaller sized industry-years will have less efficient regressors. We decided to introduce a minimum number of observations to do a regression. In calculating the Z-score we divide by (T-5), this would give a theoretical minimum of 6 observations in order to get usable results. In the end we decided to follow (Peasnell, Pope, & Young, 2000, s. 318) and require 10 observations as a minimum and exclude industry-years with fewer than 10 observations. Some industries will be affected a lot by this criterion such as the Tobacco products industry (7) that does not have a single year with sufficient observations. 1989 have so few industries with sufficient number of observations that we choose to exclude it from further calculations.

Descriptive statistics:

Table 6 shows how many observations we have in each year and industry to run our regression. That is, the number of companies in each industry, each year with enough data to run the regression. The number of companies are after excluding the ones we are investigating.

		1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
Business equipment	1	13	139	144	156	170	183	297	341	399	486	654	665	655	657	659	683	713	733	733	694	677	631	576	504	436	368	289	252	208	207	148
Fabricated products and machinery	2	3	53	53	59	62	66	90	104	114	122	171	173	159	159	158	155	165	177	179	172	164	155	147	137	122	103	90	78	67	62	52
Printing And Publishing	3	1	16	16	16	17	17	24	27	28	38	44	45	43	38	36	39	37	45	45	44	48	47	45	41	36	32	22	17	16	17	13
Retail	4	6	64	66	74	80	95	126	137	155	181	219	231	227	221	218	226	224	235	238	225	213	221	217	191	171	146	122	113	100	104	38
Petroleum and Natural Gas	5	7	36	39	44	45	48	65	73	74	92	158	175	185	205	234	259	285	309	324	322	309	292	281	258	232	186	135	110	96	87	43
Automobiles and trucks	6	2	34	36	37	40	41	49	52	53	61	74	78	85	88	90	86	83	86	83	81	79	79	77	73	63	55	45	43	37	39	30
Tobacco products	7	1	3	3	3	3	3	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5	5	6	6	6	4	4	2	2	3	1
Personal and business service	8	16	72	75	91	100	117	175	221	307	473	735	807	803	794	822	852	892	918	920	902	888	874	835	751	661	563	460	390	325	309	194
Wholesale	9	11	36	37	37	37	41	80	90	107	120	166	168	170	178	172	174	176	177	180	170	171	163	156	139	118	91	79	75	69	67	52
Everything else	10	1	3	3	3	3	4	4	3	7	9	26	27	25	27	25	26	29	31	38	37	32	30	21	18	14	11	10	9	5	5	3
Healthcare, Medical equipment & Pharmaceutical products	11	11	63	66	92	108	116	211	235	284	378	542	563	583	609	637	686	737	776	792	765	750	710	655	592	540	461	382	333	300	282	161
Food products	12	4	32	32	34	34	35	46	49	55	67	93	92	91	96	100	100	102	106	104	105	103	103	98	86	82	76	65	57	45	43	29
Banking, Insurance, Real Estate & Trading	13	42	75	80	96	102	134	141	153	160	186	232	254	265	281	337	368	399	404	415	408	402	402	411	399	418	407	369	343	326	302	223
Transportation	14	5	30	30	30	33	39	56	61	68	75	87	95	100	104	114	124	132	143	154	148	150	145	128	127	112	109	90	81	76	72	42
Communication	15	0	14	13	16	17	21	38	45	58	80	144	149	142	142	156	161	172	181	184	179	169	153	137	124	101	85	75	62	55	56	32
Construction and Construction materials	16	5	48	50	54	58	63	77	75	83	103	133	132	130	135	134	140	139	146	150	148	155	151	141	123	116	95	86	79	65	63	49
Electerical equipment	17	1	12	14	17	19	24	33	35	36	39	50	51	52	53	52	58	61	65	71	70	77	71	64	59	50	41	33	31	26	26	19
Aircrafts, Ships, and railroad equipment	18	2	12	12	11	11	13	15	19	22	26	29	30	30	33	34	35	37	39	37	35	32	29	29	26	22	20	16	16	14	12	10
Beer & Liquor	19	1	6	6	6	6	7	7	10	10	12	18	18	17	16	15	16	16	21	22	17	17	14	12	12	12	10	7	7	6	6	3
Business supplies and shipping containers	20	1	22	22	23	24	23	26	30	34	36	40	44	41	41	42	44	44	46	46	42	37	34	28	26	24	21	16	16	16	14	11
Steel works etc.	21	0	15	16	19	20	26	35	36	40	42	50	52	52	51	44	44	41	47	47	47	51	54	49	43	39	34	25	22	21	18	15
Recreation	22	3	12	14	14	15	19	36	40	47	65	115	118	121	119	125	126	129	138	143	128	118	109	108	110	87	70	56	47	39	39	20
Chemicals	23	3	30	30	32	34	34	41	42	45	56	77	81	81	84	88	89	90	105	111	111	108	106	95	90	75	60	56	54	51	45	32
Utilities	24	6	81	80	81	82	83	88	89	89	96	107	108	106	113	118	118	124	134	134	138	137	130	116	101	96	86	74	64	62	58	47
Consumer Goods	25	5	29	30	31	31	37	53	57	62	68	82	87	84	86	82	84	86	91	91	82	78	76	74	63	49	41	36	33	29	27	20
Precious metals, non-metalic, and industrial metal mining	26	1	9	9	11	10	12	17	18	20	29	41	46	50	51	53	63	77	103	109	107	110	111	118	105	89	69	56	27	24	24	16
Textiles	27	1	8	7	8	10	12	14	15	16	17	17	17	14	13	14	14	14	15	15	13	13	12	11	10	11	10	8	9	8	7	6
Coal	28	1	2	3	3	2	2	4	5	6	6	7	8	9	13	15	18	20	20	22	25	23	22	20	18	14	11	8	8	8	6	2
Resturants, hotels & motels	29	0	17	17	24	27	33	46	55	66	81	104	114	109	109	109	109	108	105	102	99	97	90	84	76	74	66	62	53	47	43	33
Apparel	30	1	13	14	16	15	16	30	32	33	33	36	37	37	38	42	45	47	48	47	46	45	42	39	34	30	24	24	19	14	14	14
No match	31	0	18	19	20	21	24	29	30	34	39	63	70	69	67	70	70	70	69	62	59	59	54	52	51	43	35	31	29	27	23	11

Table 6: show the number of observations in-sample within each industry-year

Industry	Number of company-years in regression	Number of predictions	(Predictions/ Regressions)
Business equipment	13470	696	5,2 %
Fabricated products and machinery	3568	226	6,3 %
Printing And Publishing	949	60	6,3 %
Retail	4878	447	9,2 %
Petroleum and Natural Gas	5001	582	11,6 %
Automobiles and trucks	1857	163	8,8 %
Tobacco products	0	0	0,0 %
Personal and business service	16342	526	3,2 %
Wholesale	3507	230	6,6 %
Everything else	417	29	7,0 %
Healthcare, Medical equipment & Pharmaceutical products	13420	686	5,1 %
Food products	2160	249	11,5 %
Banking, Insurance, Real Estate & Trading	8534	51	0,6 %
Transportation	2755	378	13,7 %
Communication	2961	280	9,5 %
Construction and Construction materials	3121	276	8,8 %
Electerical equipment	1309	40	3,1 %
Aircrafts, Ships, and railroad equipment	696	126	18,1 %
Beer & Liquor	255	40	15,7 %
Business supplies and shipping containers	913	159	17,4 %
Steel works etc.	1095	133	12,1 %
Recreation	2327	106	4,6 %
Chemicals	2033	228	11,2 %
Utilities	2940	633	21,5 %
Consumer Goods	1779	182	10,2 %
Precious metals, non-metalic, and industrial metal mining	1556	104	6,7 %
Textiles	267	4	1,5 %
Coal	241	16	6,6 %
Resturants, hotels & motels	2159	144	6,7 %
Apparel	924	35	3,8 %
No match	1318	46	3,5 %

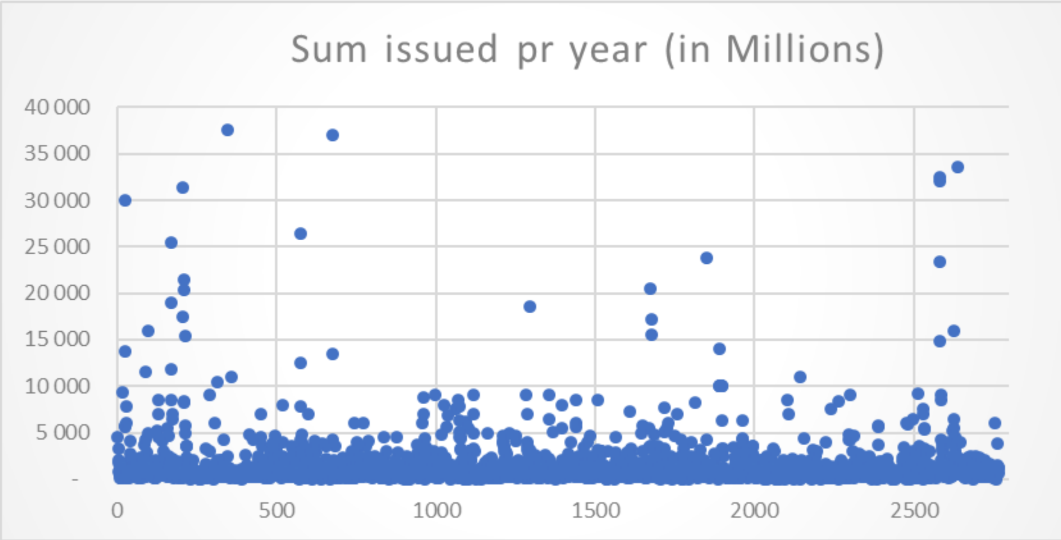
Table 7: The first column shows the number of observations within each industry that are being used in the regression. The second column shows the number of predictions within an industry. In the last column the fraction of the two are displayed. "No match" is created because we had companies with SIC codes that weren't classified in Fama-french`s industry classifications.

Year	Number of company-years in regression	number of predictions	(predictions/regressions)
1989			
1990	973	13	1,3 %
1991	1005	21	2,1 %
1992	1135	27	2,4 %
1993	1202	33	2,7 %
1994	1372	34	2,5 %
1995	1938	43	2,2 %
1996	2161	55	2,5 %
1997	2489	64	2,6 %
1998	3101	65	2,1 %
1999	4307	71	1,6 %
2000	4527	60	1,3 %
2001	4526	59	1,3 %
2002	4621	56	1,2 %
2003	4795	74	1,5 %
2004	5012	89	1,8 %
2005	5249	118	2,2 %
2006	5513	121	2,2 %
2007	5598	139	2,5 %
2008	5419	192	3,5 %
2009	5312	246	4,6 %
2010	5110	311	6,1 %
2011	4824	391	8,1 %
2012	4377	455	10,4 %
2013	3937	511	13,0 %
2014	3366	566	16,8 %
2015	2794	618	22,1 %
2016	2444	651	26,6 %
2017	2155	679	31,5 %
2018	2053	629	30,6 %
2019	1344	483	35,9 %

Table 8: Shows the number of observations within each year that we run the regression on. The next column shows how many out of sample predictions that are made within that year. Last column shows the fraction.

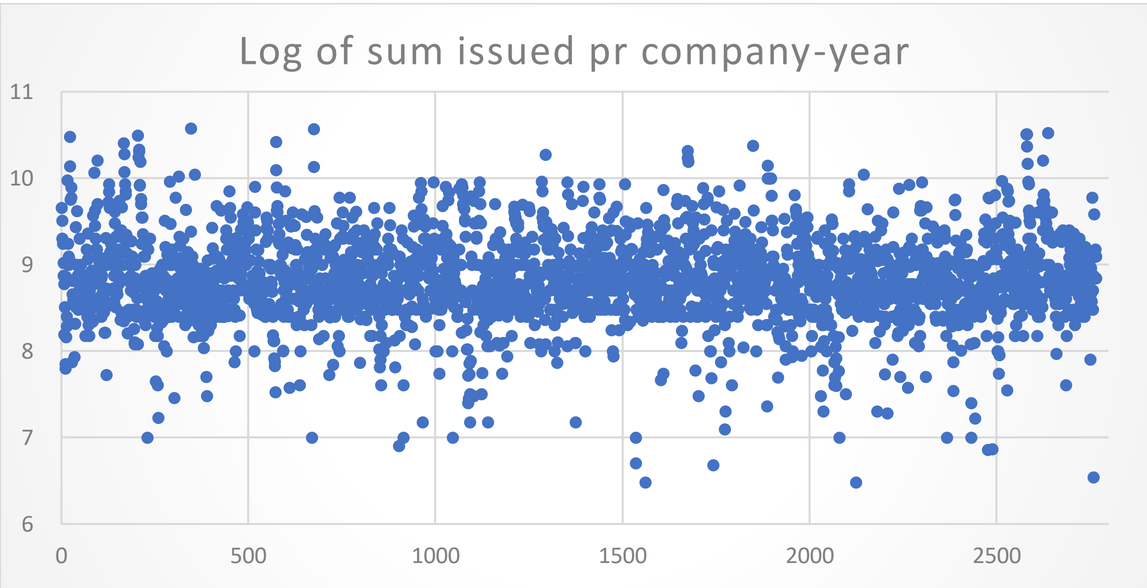
It appears that while the number of observations in the industries are somewhat evenly distributed, there are a more systematic trend within the years. We have far more data from the later companies than we do in the earlier years.

Distribution of issue size:



Graph 7 Displays bonds issue in absolute value in millions of dollars on the y-axis, within our dataset. X-axis is the observations in our dataset, not sorted by anything.

As we can see, the majority of companies issue less than $10 000 million per year and there are 9 observations above $25 000 million. To get a better understanding of the distribution we decided to look at the log of sum issued. One outlier is removed from the log version, with a "score" of 4.



***Graph 8**: Displays the log (10^y) of the bond issue size in our dataset on the y-axis, within our dataset. X-axis is the observations in our dataset, not sorted by anything.*

Omitted observations from cross-sectional regression:

Year	Omitted		Industry	Omitted
1989			Business equipment	0
1990	6		Fabricated products and machinery	1
1991	6		Printing And Publishing	1
1992	5		Retail	1
1993	4		Petroleum and Natural Gas	1
1994	4		Automobiles and trucks	1
1995	4		Tobacco products	31
1996	3		Personal and business service	0
1997	3		Wholesale	0
1998	3		Everything else	14
1999	2		Healthcare, Medical equipment & Pharmaceutical products	0
2000	2		Food products	1
2001	2		Banking, Insurance, Real Estate & Trading	0
2002	1		Transportation	1
2003	1		Communication	1
2004	1		Construction and Construction materials	1
2005	1		Electrical equipment	1
2006	1		Aircrafts, Ships, and railroad equipment	1
2007	1		Beer & Liquor	12
2008	1		Business supplies and shipping containers	1
2009	1		Steel works etc.	1
2010	1		Recreation	1
2011	1		Chemicals	1
2012	1		Utilities	1
2013	1		Consumer Goods	1
2014	1		Precious metals, non-metallic, and industrial metal mining	3
2015	4		Textiles	9
2016	5		Coal	18
2017	5		Restaurants, hotels & motels	1
2018	5		Apparel	1
2019	5		No match	1

***Table 9**: Number of omitted industry-years. Separated by year and industry, and excluded based on the need for 10 observations or more. The two columns on the left shows the number of omitted industry-years each year. The two columns on the right shows the number of industry-years that are omitted from each industry*

6 Empirical Analysis

This chapter is divided up in three parts, risk-shifting, earnings management and an analysis of whether the same companies engage in risk-shifting and earnings management. First, we introduce risk-shifting, where we look at average asset volatility, then we look at Levenes test to see if there are a significant difference and at last, we implement a 1-year Merton model as a robustness test.

Part two starts off with a brief discussion on some difficulties with conducting earnings-management test. We then present results from the cross-sectional model, we discuss problems regarding robustness, outlier problems and heteroskedasticity within this model. We then look at another model which group companies based on company size, we also analyze heteroskedasticity, outlier and end with a general discussion of the model. To cope with some of the problems regarding the cross-sectional model and decile divided model we implemented a panel data model.

In the last part we check whether we can find a relation between earnings management and risk-shifting.

6.1 Risk-shifting

We start with presenting the average volatility. The next step is to implement Levenes-test, to test whether the volatilities in the years surrounding issue year is significantly different from the volatility in year zero (issue year).

6.1.1 Average Volatility from the T-year Merton model

	Year -2	Year -1	Year 0	Year +1	Year +2
Number of observations (n)	186	200	214	220	190
Average volatility	34,4 %	36,4 %	35,7 %	47,2 %	42,8 %

Table 10: Displays number of companies (n) we were able to conduct asset value calculations on that specific year in the event study, and the average standard deviations below.

There is a big increase in volatility after debt issue. The volatility appears stable until after debt has been issued. A stable average volatility until after debt issue indicates that the change is not accidental. It also appears that the volatility declines after some time

There could be individually differences between industries in our data set. We divided the companies based on their Fama-French industry classifications code and calculated the average volatility throughout the event period.

Industry divided - Average standard deviation	-2	-1	0	1	2
Business equipment	28,0 %	43,4 %	28,2 %	49,0 %	56,3 %
Fabricated products and machinery	28,6 %	28,8 %	34,3 %	45,8 %	44,4 %
Printing And Publishing	19,4 %	18,5 %	21,1 %	52,5 %	55,5 %
Retail	29,2 %	25,1 %	28,3 %	52,9 %	47,7 %
Petroleum and Natural Gas	70,1 %	49,2 %	60,6 %	46,8 %	42,4 %
Automobiles and trucks	34,0 %	33,5 %	22,2 %	47,3 %	44,9 %
Tobacco products	18,6 %	88,3 %	12,0 %	32,6 %	28,5 %
Personal and business service	43,8 %	34,8 %	19,7 %	36,5 %	30,1 %
Wholesale	21,5 %	25,0 %	22,5 %	47,1 %	42,0 %
Everything else	77,3 %	20,8 %	70,0 %	50,9 %	41,3 %
Healthcare, Medical equipment & Pharmaceutical products	30,2 %	29,3 %	27,3 %	31,9 %	25,4 %
Food products	19,6 %	17,1 %	16,6 %	24,5 %	29,9 %
Banking, Insurance, Real Estate & Trading		39,9 %	44,9 %	50,7 %	28,1 %
Transportation	24,2 %	28,3 %	17,4 %	45,8 %	36,4 %
Communication	24,4 %	50,7 %	48,5 %	44,8 %	62,0 %
Construction and Construction materials	36,7 %	31,8 %	26,0 %	40,9 %	44,3 %
Electerical equipment	24,0 %	22,0 %	42,5 %	69,1 %	49,0 %
Aircrafts, Ships, and railroad equipment	11,5 %	19,8 %	13,8 %	29,1 %	39,7 %
Beer & Liquor	27,3 %	17,5 %	16,9 %	20,8 %	18,2 %
Business supplies and shipping containers	22,5 %	44,0 %	28,4 %	40,5 %	31,7 %
Steel works etc.	31,2 %	46,2 %	35,8 %	68,7 %	62,6 %
Recreation	32,7 %	29,5 %	20,7 %	50,5 %	53,0 %
Chemicals	26,5 %	30,4 %	27,9 %	51,0 %	60,0 %
Utilities	22,5 %	32,6 %	33,2 %	50,5 %	36,1 %
Consumer Goods	26,1 %	22,1 %	26,9 %	42,9 %	27,2 %
Precious metals, non-metalic, and industrial metal mining	64,2 %	56,0 %	62,1 %	58,6 %	44,3 %
Textiles					
Coal					
Resturants, hotels & motels	18,7 %	18,7 %	23,6 %	60,2 %	37,4 %
Apparel	22,7 %	20,8 %	21,8 %	13,3 %	14,5 %
No match	41,6 %	44,5 %	93,5 %	83,8 %	35,9 %

Table 11: Displays the average standard deviations for each industry the different years in the event-study.

A lot of the industries have few observations and therefore uncertainty regarding their results, table 12 shows the number of observations per industry. We put a threshold of 10 observations for further inspection, the green cells in table 12. Petroleum and natural gas go against the overall results and have a declining volatility after the event year. Further retail has a massive jump in volatility after debt issuing. Same for utilities but have a decline two years after issue compared to one year after issue.

Number of observations (n)					
Industry	-2	-1	0	1	2
Business equipment	14	17	17	16	14
Fabricated products and machinery	7	7	8	10	9
Printing And Publishing	2	1	3	3	3
Retail	13	14	15	17	15
Petroleum and Natural Gas	12	14	15	14	11
Automobiles and trucks	4	6	6	7	4
Tobacco products	2	2	2	3	3
Personal and business service	7	7	6	7	7
Wholesale	6	6	7	7	5
Everything else	1	1	2	2	2
Healthcare, Medical equipment & Pharmaceutical products	22	23	22	22	21
Food products	5	5	6	8	6
Banking, Insurance, Real Estate & Trading	0	3	3	3	3
Transportation	11	11	12	12	11
Communication	8	8	8	10	8
Construction and Construction materials	7	7	8	8	8
Electerical equipment	2	2	3	3	2
Aircrafts, Ships, and railroad equipment	2	2	2	2	2
Beer & Liquor	2	2	3	3	3
Business supplies and shipping containers	6	6	6	6	6
Steel works etc.	4	4	4	4	4
Recreation	1	2	2	3	3
Chemicals	5	5	6	6	8
Utilities	27	27	29	26	19
Consumer Goods	4	5	6	5	3
Precious metals, non-metalic, and industrial metal mining	6	6	6	6	6
Textiles	0	0	0	0	0
Coal	0	0	0	0	0
Resturants, hotels & motels	3	4	4	4	3
Apparel	1	1	1	1	1
No match	3	3	3	3	2

Table 12: displays the number of companies in the different industries, the different years. Marked green if there are a reasonable number of observations to conduct the average calculations.

6.1.2 Levenes-test T-year Merton model

	5% significance level-Significant if F-value> 3,84							
	$\sigma_{-2} > \sigma_0$	$\sigma_{-2} < \sigma_0$	$\sigma_{-1} > \sigma_0$	$\sigma_{-1} < \sigma_0$	$\sigma_1 > \sigma_0$	$\sigma_1 < \sigma_0$	$\sigma_2 > \sigma_0$	$\sigma_2 < \sigma_0$
Significant	92	41	111	29	141	20	97	36
Not significant	14	36	30	27	17	26	14	22
Total	106	77	141	56	158	46	111	58

Table 13: displays number of companies that have higher or lower volatility relative to year 0 in the event study. Example: $\sigma_{-2} > \sigma_0$. Tells us how many companies that have higher volatility in year -2 than in year 0. Further it shows if the volatility for each company is significantly different or not using the Levens-test on each company. The significance level and necessary F-value are displayed at the top.

We find that all years have a majority of companies with significantly higher volatility than in the issue year. Except from two year prior to issue this finding is in alignment with the results from average volatility. The misalignment in year -2, might stem from a few companies in either year -2 or 0 with extreme volatilities. We do find a surprisingly large portion of companies with higher volatility prior to debt issue.

We find the highest percentage of companies with significantly higher volatility one year after debt is issued. This is aligned with our results from the average volatility. The big portion of companies being significantly higher suggest that there are risk-shifting tendencies.

The number of companies with higher volatility declines from one year after debt issue to two years after issue, but still the majority have higher volatility. A possible explanation for the reduction could be that some of the companies would be closing in on their next debt issue and therefore reduce their volatility.

Both the average volatility and Levenes-test gives support to hypothesis 1.1, there seems to be an increase in volatility after debt has been issued.

To answer hypothesis 1.2 we divided the result from table 13 into two tables. Table 14 consist of companies with several bond issues, and table 15 contains companies with only one issue.

	5% significance level-Significant if F-value> 3,84							
	$\sigma_{-2} > \sigma_0$	$\sigma_{-2} < \sigma_0$	$\sigma_{-1} > \sigma_0$	$\sigma_{-1} < \sigma_0$	$\sigma_1 > \sigma_0$	$\sigma_1 < \sigma_0$	$\sigma_2 > \sigma_0$	$\sigma_2 < \sigma_0$
Significant	84	37	98	27	126	16	86	35
Not significant	8	31	28	20	16	24	13	20
Total	92	68	126	47	142	40	99	55

Table 14 displays number of companies that have issued several bonds and whether they have higher or lower volatility relative to year 0 in the event study.

	5% significance level-Significant if F-value> 3,84							
	$\sigma_{-2} > \sigma_0$	$\sigma_{-2} < \sigma_0$	$\sigma_{-1} > \sigma_0$	$\sigma_{-1} < \sigma_0$	$\sigma_1 > \sigma_0$	$\sigma_1 < \sigma_0$	$\sigma_2 > \sigma_0$	$\sigma_2 < \sigma_0$
Significant	8	4	13	2	15	4	11	1
Not significant	6	5	2	7	1	2	1	2
Total	14	9	15	9	16	6	12	3

Table 15 displays number of companies that have issued only one bond and whether they have higher or lower volatility relative to year 0 in the event study

First thing we see is that companies which issue only one bond is around 10% of companies we have done a risk-shift analysis of. From table 13 we saw that 69,1% of companies which we have analyzed one year after issue, had significantly higher volatilities. When looking at table 14 which is companies issuing several bonds, we find that 69,2% of companies which we have analyzed one year after issue, had significantly higher volatilities. Table 15 which is companies only issuing one bond, tells us that 68% of companies which we have analyzed one year after issue, had significantly higher volatilities. There is no indication of companies that only issue once, having a higher percentage of the sample with significantly higher volatilities. Hypothesis 1.2 is rejected.

Too answer hypothesis 1.3 about the leverage risk-shifting relation we grouped the companies in 4 quartiles with 25% in each group. Quartile 1 being the group with highest leverage ratio, and group 4 is the companies with lowest leverage ratio. Table 16 looks at the relation between high leverage and risk-shift. The table shows how many observations from each quartile that have volatilities which is significantly higher than the volatility in year zero each year of the event period.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Year -2	22	24	21	21
Year -1	31	32	23	23
Year 1	38	45	31	27
Year 2	26	35	17	19

Table 16 the number of companies in each quartile with significantly higher volatility compared to issue year. With a 5% significance level demanding F-value above 3.84

As we can see quartile 1 and 2 have more observations where volatility is significantly higher in year one than zero. In accordance with table 13, we find that the number of significantly higher volatilities increase from two year prior to one year prior to issue. It is also worth noting that quartile 4 has the lowest number of significant companies. There isn't conclusive evidence supporting the hypothesis of higher levered companies increasing volatility more after debt issue. There are however indications that companies with higher leverage generally have higher volatility in years surrounding debt issue.

6.1.3 1-year model as a robustness test of the T-year model

A big challenge when conducting the Merton model is predicting time to maturity. Although assuming short term debt has an average maturity of half a year and long term debt has an average of 10 years can be viewed as reasonable, it brings uncertainty. Accrued dividend and interest payments made at time T also brings uncertainty. (Löffler & Posch, 2007) presents a 1-year Merton model to calculate the asset values and volatilities.

We conducted these calculations as a robustness check to see how the assumptions of always 1-year time to maturity would affect our results. This model assumes that there are no dividends or interest payments within the one year to maturity.

Average standard deviation				
-2	-1	0	1	2
27,8 %	27,0 %	28,1 %	23,6 %	23,4 %

Table 17: Displays the average standard deviation each year in the event study from the Merton 1-year model.

The volatilities drop after the issue year. This most likely happens because the equity would become more volatile as the issuing date approaches because time to maturity of existing debt would decline. When the debt is issued time to maturity would increase and equity volatility would drop. If the model does not correctly account for the change in maturity the declined equity volatility would be calculated as if this was a consequence of reduced asset volatility. As the 1-year model causes a drop in volatility and T-year causes an increase there could be that one overestimates and the other underestimates the maturity effect on asset volatility.

6.2 Earnings-management

6.2.1 Conducting the tests

There are thirty years and thirty-one industries giving a total of 930 regressions, because of this we will not present individual regressions in our thesis.

If a company has issued two or more bonds sequentially or within a 5-year period of each other, will have an overlap in the event study. An example, if a company issues a bond in year 2005 and 2008 the observations from years 2006 and 2007 will be listed as year +1 and +2 in one timeline and year -2 and -1 in another timeline. This will cause the significance to decline as the averages will be closer together with the same observation in several years in the event years.

An example of a company causing problems in our dataset is General Electric, which we have over 300 individual bonds from. This means that they will have several observations every year, and the same observations in every year in the event study. To reduce problems regarding several issues in a year, we summarized the amount issued by a company within a year.

The approach is to run the regressions to get every companies discretionary accruals from 1990 to 2019. We will then group companies according to different scenarios which we want to investigate. We will be presenting each analysis individually and give an interpretation on the results.

6.2.2 Cross-sectional model

As discussed, our analysis is an event study with issuing of bonds as year zero. We choose two years prior and after to get an idea of the differences between the years. We use Z-scores (equation 3.16) and the average prediction error to present the results from each year in the event-study. We assume a Gaussian distribution when calculating p-values and significant levels.

Table 18 and 19 displays the Z-values and average prediction errors for all scenarios we have investigated. We will be commenting and discussing each analysis, to explain what has been done and a discussion regarding the results. Throughout this chapter -2 represents two year prior to issue of debt, -1 represents one year prior, and so on.

Criteria	-2	-1	0	1	2
Base case	0,849	0,966	1,136	0,910	0,532
Excluding industry 10 & 31	0,827	0,921	1,093	0,797	0,476
Biggest issue (relatively)	0,168	0,558	0,637	0,350	-0,489
Only 1 bond issued	-0,393	1,010	0,468	-0,540	-0,218
Bond size less than $350 mil	-0,112	0,158	1,019	-0,042	-0,022

(1st quantile)					
Bond size between $350-600 mil (2nd quantile)	0,216	0,509	0,102	-0,107	0,122
Bond size between $600-1250 mil (3rd quantile)	0,797	0,589	0,335	1,176	0,274
Bond size above $1250 mil (4th quantile)	0,801	0,684	0,817	0,805	0,717

*Table 18: displays the Z-values each year in the event-study under the different scenarios. Our test is a one-sided t-test and we mark the results which are significant at 1%, 5% or 10% significant level with ***,** or *.*

Average Prediction errors	-2	-1	0	1	2
Base case	1,27	0,72	0,70	0,75	0,66
Excluding ind. 10 & 31	1,44	0,79	0,76	0,76	0,77
Only 1 bond issued	0,99	0,92	0,66	0,59	0,09
Biggest issue relatively	0,17	0,56	0,64	0,35	-0,49
Bond size less than $350 mil (1st quantile)	0,50	0,41	0,53	0,39	0,08
Bond size between $350-600 mil (2nd quantile)	0,22	1,64	0,64	0,06	1,73
Bond size between $600-1250 mil (3rd quantile)	2,21	0,39	1,20	1,81	0,14
Bond sizes above $1250 mil (4th quantile)	2,15	0,47	0,41	0,75	0,77

Table 19 displays the average prediction errors the different years in the event-study under the different criteria

We start the analysis with our base case. The base case consists of prediction errors from all companies in our data sample which has issued debt.

Base case	-2	-1	0	1	2
Average prediction error	1,27	0,72	0,70	0,75	0,66
Median prediction error	0,04	0,02	0,00	0,00	0,01
Z-values	0,85	0,97	1,14	0,91	0,53

Table 20: displays the average prediction -error and -median, and the Z-values for each year in the event study under the criteria.

The Z-values show a trend with the highest score in year 0, they are however not significantly different from zero. The average prediction errors move in the opposite direction of the Z-values from year -2 to +1. The higher Z-values in year zero are therefore caused by other factors than average prediction errors. The way Z-values are calculated, an increase in observation (ceteris-paribus) would give an increased Z-value. Our base case includes all industries from Fama-French and one industry with the companies that weren't categories in Fama-French. This means our base case includes Fama-French`s "everything else" and our "no match". An assumption in the cross-sectional regression is homogenous companies, it is unlikely that companies in industry 10 and 31 are homogenous. We will therefore remove these two industries from further analysis.

Base case excluding 10 & 31	-2	-1	0	1	2
Average prediction error	1,44	0,79	0,76	0,76	0,77
Median prediction error	0,03	0,02	0,02	0,01	0,01
Z-values	0,827	0,921	1,093	0,797	0,476

Table 21: displays the average prediction -error and -median, and the Z-values for each year in the event study under the criteria.

Yet again we see Z-values and average prediction error move in different directions and yet again we see no significant Z-values. Further we see an increase in average prediction error in all years compared to the base case. Although the Z-values has the expected pattern, the lack of significance and average prediction error moving in the opposite direction leads us to conclude that there isn't strong enough evidence of systematical earnings management. We therefore reject hypothesis 2.1. One reason for the lack of significant result can be that there are more instances where companies doesn't have enough incentives. To investigate this, we are going to look at whether companies engage in earnings management before their biggest bond issue. We believe the bigger the bond the bigger the incentive.

We are going to investigate the relatively biggest issue. When the relatively issue size is larger the "reward" for engaging in earnings management would be larger as the yield would be a relatively bigger part of your future cash flow. We calculated the relatively biggest issue by dividing the annual issue size by the lagged assets. As lagged assets are the variable used to create relative sizes in order to reduce heteroskedasticity in the Jones-model it seemed appropriate to use as denominator in the relative size fraction. There are other variables that might work for example market size. We used the *lagged* value as assets would otherwise be affected by the debt issue itself, and therefore cause multicollinearity.

Biggest issue (relatively)	-2	-1	0	1	2
Average prediction error	0,50	0,41	0,53	0,39	0,08
Median prediction error	0,02	0,01	0,01	0,01	0,02
Z-values	0,17	0,56	0,64	0,35	-0,49

Table 22: displays the average prediction -error and -median, and the Z-values for each year in the event study under the criteria.

The Z-values are reduced, probably caused by lower number of observations. This time the average prediction errors show a pattern matching the Z-values with the highest values in year 0 but have only slightly higher values in year 0 compared to year -2. The Z-values are not significant, and the much lower medians are once again indicating large outliers. Without significant results we must reject hypothesis 2.3.

As discussed in the theory section, in order to conduct earnings management using accruals a company needs to move earnings from one year to another, meaning that the total earnings over several years should remain the same. Because of this principle it would make less sense to engage in excessive earnings management if a company have sub-sequent bond issues. The exception would be earnings smoothing, but it would be harder for us to detect as the accruals would in some issue years be negative and others positive. We therefore wanted to check how companies that only issue in a single year would behave.

Only one bond issued	-2	-1	0	1	2
Average prediction error	2,23	0,54	0,55	1,12	0,50
Median prediction error	0,03	0,02	0,01	0,00	0,00
Z-values	-0,39	1,01	0,47	-0,54	-0,22

Table 23: displays the average prediction -error and -median, and the Z-values for each year in the event study under the criteria.

For the first time year 0 does not have the highest Z-value. The pattern is somewhat similar, but this time the highest value is observed in year +1. The average prediction error and the Z-values have opposite values, in 3 out of 5 years. A possible explanation for this may be caused by standard deviation of the prediction errors that reduced certain large positive prediction errors, but did not reduce the negative prediction errors as much. This could cause the Z-values to be negative while the average prediction errors remained positive. The average is once again way higher than the median and therefore looks like there are large outliers. We do not have significant Z-values and the average prediction errors do not give a clear pattern, and therefore reject hypothesis number 2.2.

To get a better understanding on how bond size affected the results, we divided the annual absolute issue size into four quartiles. From graph 7, it is clear how big the differences are in the fourth quartile, where the largest issue years from in the dataset are closer to 40 billion dollars and the last quartile starts at 1,25 billion dollars.

Bond size less than $350 mil (1st quartile)	-2	-1	0	1	2
Average prediction error	0,22	1,64	0,64	0,06	1,73
Median prediction error	0,04	0,04	0,01	0,00	0,02
Z-values	-0,11	0,16	1,02	-0,04	-0,02
Bond size between $350-600 mil (2nd quartile)	**-2**	**-1**	**0**	**1**	**2**
Average prediction error	2,21	0,39	1,20	1,81	0,14
Median prediction error	0,03	0,02	0,02	0,02	0,01
Z-values	0,22	0,51	0,10	-0,11	0,12
Bond size between $600-1250 mil (3rd quartile)	**-2**	**-1**	**0**	**1**	**2**
Average prediction error	2,15	0,47	0,41	0,75	0,77
Median prediction error	0,04	0,03	0,02	0,02	0,01
Z-values	0,80	0,59	0,33	1,18	0,27
Bond sizes above $1250 mil (4th quartile)	**-2**	**-1**	**0**	**1**	**2**
Average prediction error	1,85	0,49	0,42	0,76	0,79
Median prediction error	0,04	0,03	0,02	0,02	0,01
Z-values	0,80	0,68	0,82	0,81	0,72

Table 24: displays the average prediction -error and -median, and the Z-values for each year in the event study for each of the four quartiles. The quartiles are divided by absolute value of the Bond issue size over the course of one year.

In the first quartile there appears to be a big increase in year 0, but not a statistically significant result. In the second quartile the biggest Z-value is found one year prior to issue. The difference is much smaller, and the curve appears flatter than the first quartile. The data from the third quartile seems to be random and without any pattern that we can explain. The fourth quartile is the flattest curve yet and all the Z-values are relatively high, but none of them are significant. Again, they are all positive.

Looking at the average prediction errors we find that the patterns are not very consistent with the reported Z-values. It appears that the changes in the Z-values are more often caused by changes in other factors than the average prediction errors. The first quartile is the one with the most interesting Z-values, but with the average prediction errors being inconsistent it's hard to make any conclusions.

It appears that the bigger the issue size the higher the Z-values are. This could be caused by a flaw in our model. A possible explanation is that the model underestimates the accruals from big companies, and that this is causing the estimated discretionary accruals from companies with big issues to be too high. There are several places in our model that should work to reduce this bias. The first is the model itself, where the constant should increase the expected accruals if the relationship between size and accruals are proportionally constant. The second place in the models are through the standard deviation of the prediction error. If the biggest bonds are issued by the companies having out of sample X-values above the in-sample X-values, the standard deviation of the prediction error should increase, causing lower V-values. The third way our model work is that we only exclude the companies from the regressions the five years we use when they issue bonds. It could however be that big companies issue more bonds and are therefore excluded a lot of the years.

6.2.3 Industry specific analysis

Industy	-2	-1	0	1	2
Business equipment	0,49	0,36	0,23	0,37	0,15
Fabricated products and machinery	0,27	0,69	0,15	-0,47	0,15
Printing And Publishing	-0,76	-0,36	-0,21	-0,20	-1,10
Retail	-0,01	0,78	0,87	0,27	0,18
Petroleum and Natural Gas	0,25	0,12	0,14	-0,08	0,02
Automobiles and trucks	0,78	0,99	0,45	0,27	1,13
Tobacco products					
Personal and business service	0,64	0,51	0,49	0,39	0,27
Wholesale	1,55	1,56	2,37	1,66	1,16
Everything else	0,72	0,95	0,74	1,29	0,66
Healthcare, Medical equipment & Pharmaceutical products	0,03	0,25	-0,08	-0,11	-0,21
Food products	0,27	0,21	-0,02	0,67	0,02
Banking, Insurance, Real Estate & Trading	0,11	-0,02	-0,27	0,08	0,37
Transportation	0,77	0,97	0,83	0,66	1,20
Communication	0,17	0,13	-0,11	0,02	0,20
Construction and Construction materials	-0,87	0,03	0,23	-0,50	-0,67
Electerical equipment	0,04	-0,70	0,17	0,19	0,09
Aircrafts, Ships, and railroad equipment	0,21	0,35	0,34	0,90	0,15
Beer & Liquor	-0,27	-0,27	0,12	0,07	-0,28
Business supplies and shipping containers	-1,64	-2,97	-1,14	-1,69	-1,11
Steel works etc.	-1,02	-0,90	-1,03	-0,34	-0,49

Recreation	-0,06	0,28	0,00	0,05	-0,03
Chemicals	0,29	0,10	0,44	0,13	0,34
Utilities	1,29	0,62	0,86	1,14	1,05
Consumer Goods	-0,07	-0,48	-0,42	-0,92	-1,85
Precious metals, non-metalic, and industrial metal mining	-0,08	-0,18	-0,07	0,07	-0,16
Textiles	-0,07	-0,64	-0,21	-0,16	
Coal	0,90	-0,08	-0,01	-0,18	-1,91
Resturants, hotels & motels	-0,40	0,30	-0,41	-0,23	0,27
Apparel	-1,00	-0,18	0,18	1,17	0,30

Table 25: Z-values calculated for each industry and each event year.

The industry specific table is sorted by industry in order to see if there are any industries with interesting results. The only industry with statistically significant results is wholesale (9). Looking at table 6 the significant results are not caused by having a lot more predictions than the other industries. Business supplies and shipping containers on the other hand, gives us very negative values.

6.2.4 Year specific analysis

Issue Year	Year nr	-2	-1	0	1	2
1990	2			-0,44	0,22	-0,28
1991	3		-0,72	-1,56	-0,36	0,07
1992	4	-0,32	-0,59	0,07	-0,47	0,11
1993	5	-0,25	-0,61	-0,62	-1,21	-1,23
1994	6	0,10	0,27	-1,37	-0,42	-0,61
1995	7	-2,10	-1,09	0,56	-0,63	-0,09
1996	8	-0,41	-0,58	-0,25	-0,27	0,19
1997	9	0,18	0,72	0,57	-0,31	0,20
1998	10	-0,35	0,34	-0,34	0,58	0,77
1999	11	0,38	0,46	0,17	0,69	0,38
2000	12	-0,16	0,81	0,96	0,68	-0,09
2001	13	0,58	0,95	0,31	0,43	0,23
2002	14	0,71	0,35	0,32	0,12	0,35
2003	15	0,45	-0,22	0,40	0,44	0,24
2004	16	0,39	0,42	0,43	0,45	-0,16
2005	17	0,27	0,23	0,22	-0,57	0,57
2006	18	0,25	0,12	-0,46	0,85	0,67
2007	19	-0,24	0,11	1,09	0,71	0,33
2008	20	-0,46	0,84	0,19	0,24	0,22
2009	21	0,29	0,16	0,24	0,19	0,14
2010	22	0,50	0,32	0,27	0,31	-0,26
2011	23	0,30	0,15	0,37	-0,31	0,78
2012	24	0,15	0,22	-0,20	0,17	-0,07
2013	25	0,12	-0,39	0,50	0,25	0,27
2014	26	-0,38	0,78	-0,01	0,22	0,32
2015	27	0,81	0,17	0,55	1,22	0,41
2016	28	0,18	1,00	1,17	1,06	-0,95
2017	29	0,94	1,08	0,64	-1,11	0,21

2018	30	0,10	-0,26	-0,99	0,46
2019	31	0,13	-0,74	0,85	

Table 26: Displays the Z-values the different years in the event study, for each year in the sample

As with the industries we wanted to see if some years had bigger deviations than others. When having a lot of analyzes there is expected to find some years with some deviations from zero. This is also the case as there are some years with bigger deviations from zero. There are however not any years giving sensational deviations.

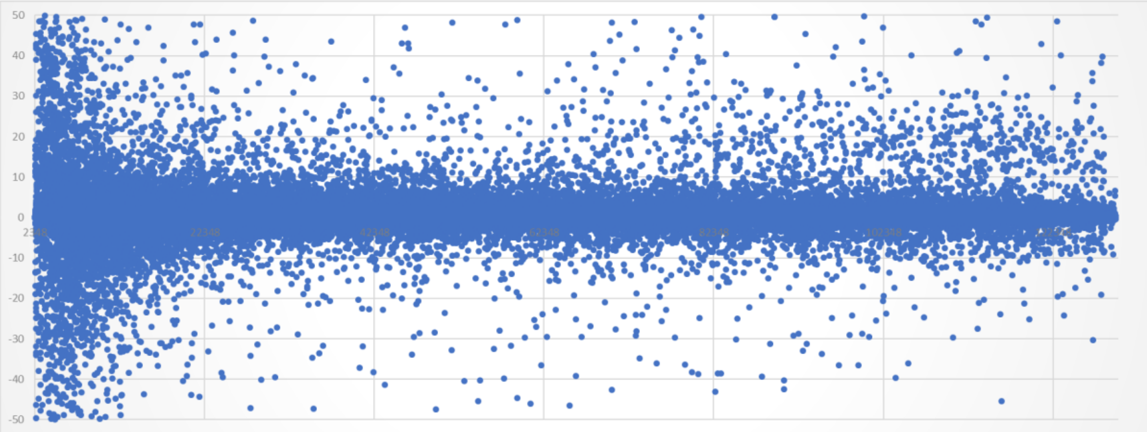
Including the quartile, industry and years specific data does not provide any deeper insight in earnings management, but they serve as a robustness check, to see if any quartile, any certain industries or years contribute a lot to the results.

6.2.5 Robustness of the cross-sectional model

According to theories from (Jones, 1991) and (Sloan, 1996) we should find the discretionary accrual relative to the lagged asset value through a prediction model. As we make the regressions on the in-sample values we wanted to check how well the model fits the in-sample reported total accrual calculations. The average R^2 from the 930 cross-sectional regressions is 57%. A complete table with R^2 numbers are included in the appendix 2.

Based on the composition of total assets (appendix 3) the discretionary accruals should from economic understanding not be deviating to far from -1 to 1. The reason is that the accruals should be a part of a company's assets. As the accruals are calculated from a certain year's cash flow and divided by the lagged assets, some cases with values exceeding -1 and 1 are expected. Looking at the relative accruals in the dataset there are outliers much more often than what is expected and with deviations exceeding the expectations. Often the high relative accruals are caused by low reported total assets while reporting high earnings and cashflows. There are cases where it is reported as zero, which break the fraction, and sometimes around zero causing astronomical relatively accruals in our dataset compared to other companies.

The problem then transfers into our predictions because of low accuracy when the residuals (in-sample errors) are huge. We plotted the residuals against lagged assets to get an overlook at the outlier problem (shown in graph 9). The graph has 101 235 observations where the majority are around the expected level, but the model do often predict catastrophically wrong. The Y-axis is cut off with a range of (-50,50) but there are outliers far exceeding these numbers with 1487 observations laying above fifty or below minus fifty. As the model tries to predict what the non-discretionary accruals should be, accuracy is of importance. While the potential earnings management may be of a few percent of total assets, it would be harder to separate the actual earnings management as the standardized prediction errors would decline from higher standard errors caused by huge outliers.



Graph 9: Displays the in-sample residuals. The y-axis shows the residual value. The observations are sorted on smallest to biggest asset value and do therefore not display size of total assets in our dataset, but rather the rank from smallest to biggest.

Too check for how severe the outlier problem is and how they affect our results we checked the skew and kurtosis statistic for the in-sample residuals.

Test	Cross-sectional
Skew	-137
Kurtosis	34 151

Table 27: displays the skew and kurtosis in the Cross-Sectional model.

Both the skew and kurtosis report massive numbers. Where a normal distribution would grant a kurtosis value of 3, 34 151 is an astronomical number. The results from the two tests clarify the outlier problem in our dataset. The outliers that are in the thousands could heavily affect these results.

(Jones, 1991) includes asset value to tackle the problem with heteroskedasticity through using lagged assets to create relatively values in both exogenous and endogenous variables. Graph 9 above may also be used to look for heteroskedasticity and it is a clear pattern of the biggest residuals being from the observations with lower lagged asset value.

We conducted the Whites test for heteroskedasticity presented in (Wooldridge, 2014, s. 223). The test is conducted cross-sectional to see if residuals are correlated across the entire dataset. Meaning that all the in sample total accruals and the residuals are in the same regression. Whites idea is that if there are no heteroskedasticity, the coefficients should not have any explanatory power and we therefore F-test to see if they are zero. The results strongly support what can be seen from the graph 9 with a F-stat of 1974.

res_sq	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yhat	-5779.673	105.8532	-54.60	0.000	-5987.143	-5572.202
yhat_2	.0442349	.0043103	10.26	0.000	.0357869	.052683
_cons	6121.631	22913.15	0.27	0.789	-38787.85	51031.12

Table 28: Displays the results from conducting a Whites test. The yhat is the insample predicted values while yhat_2 represent the predicted values squared. They are then regressed on the squared in sample residuals. The test F-stat would then tell us if the predicted values have explanatory power on the expected residuals. The test is conducted across the entire dataset and therefore contains residuals and predictions from all the regressions in the decile model.

From the coefficients, huge squared residuals are expected from the companies with the lowest (most negative) estimated total accruals. As the estimated total accruals squared are positive, higher estimated accruals would slow the decline in expected squared residuals, but as the coefficient is much lower it is not likely that there are expected larger heteroskedasticity from the higher estimated values. Deriving the Whites test confirms this, with a low point at about 130 000.

6.2.6 General discussion

Because of the trouble finding decent Z-values and average prediction errors, together with the robustness check of this model we find it unfit to yield any decent results. Some problems are strong indications of heteroskedasticity in the prediction models which breaks OLS-assumptions. Further it appeared the model failed to give us an expected prediction error at Zero which was an assumption to conduct the Z-value calculations.

6.3 Decile model

Because of the seemingly increased Z-values from the bigger issue sizes, we were wondering if the regressions properly adjust for the size of the companies. Further the in-sample residuals seems to be much bigger for the smaller asset sizes indicating that the relative total accruals may be different depending on the size of the company. The relation between asset size and accruals may not be proportionally constant, causing a big bias if company sizes in the regressions and the predictions are different. Another problem is that if the asset value lay far above (below) the average asset value in the regressions, the standard deviations of the prediction errors would go up. Potential significant results could be severely reduced by large error-terms.

We wanted to conduct a new regression to see how grouping the companies different would affect our results. We used year specific as earlier but grouped our companies into ten deciles, each representing ten percent of the companies that year. We divided them based on the lagged assets variable to divide them by size. The equation is almost identical to equation (3.15) but the industry specification “j” has been changed to decile specification “d”.

$$u_{idt} = \left(\frac{TA_{idt}}{A_{idt-1}}\right) - \left[\alpha_{dt}\left(\frac{1}{A_{idt-1}}\right) + \beta_{1dt}\left(\frac{\Delta REV_{idt}}{A_{idt-1}}\right) + \beta_{2dt}\left(\frac{PPE_{idt}}{A_{idt-1}}\right)\right] \qquad (6.1)$$

There could be several other variables that could work as a divider, like market value or bond issue size instead of the lagged assets. We did not want the new debt to be included in the assets value, and therefore used lagged assets as the variable used to sort them. This time the companies in industry 10 and 31 are not excluded as the basis is not industry but rather size.

From the calculations it became clear that most of the bonds by far are issued from the larger companies. While this is not surprisingly, the difference was still larger than anticipated. We don’t have any data suggesting a single bond was issued for the smallest ten percent over the entire period from 1989 to 2019, while 47,5 percent of the bonds are issued from the top ten percent biggest companies. As the lowest deciles does not issue bonds, and there are indications that the coefficients are not proportional constant, using the smallest companies in the regressions might cause a bias in the cross-sectional model.

Decentile	Percent
1	0,0 %
2	0,2 %
3	0,3 %
4	1,0 %
5	2,9 %
6	5,0 %
7	7,8 %
8	12,1 %
9	23,1 %
10	47,5 %

Table 29: Displays the percentage number of bonds in our dataset found in the different deciles.

The deciles are year specific, meaning that the deciles are calculated from the observations that year. This causes a situation where a company can be in different deciles in different years. Dividing into ten equally big deciles, gives each year and deciles more companies to run the regressions on, than when dividing into years and industry. With 10 deciles and 31 years, totaling to 310 individual regressions, opposed to 930 regressions from the cross-sectional model. With much fewer regressions, there are not any problem finding enough companies for each decile-year. The lowest number of observations are in the year 1989 with the lowest decile having 102 observations. There is a large portion of the companies in certain decile-years that issue bonds. Some years in the tenth decile there are more companies issuing bonds than there are not issuing. Causing the number of predictions to be higher than the number of companies used to run the regression.

As with the cross-sectional model we included the complete R^2 table for all decile-years in the appendix 2. The average R^2 is 28% in the decile model.

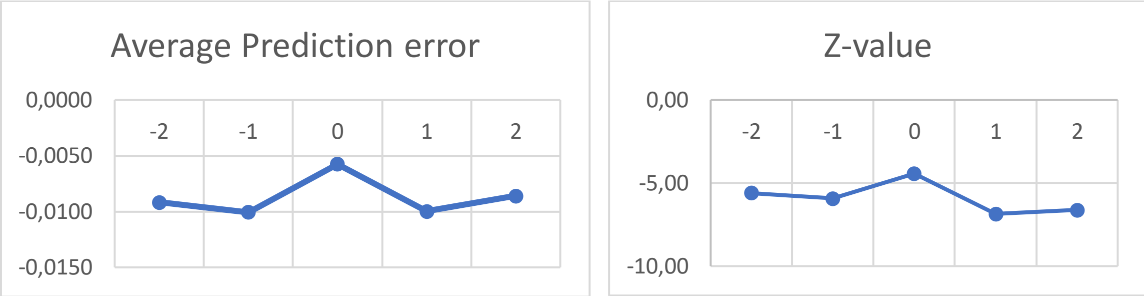
6.3.1 Base case

As we did in the cross-sectional model, the observations where a company has issued several bonds in the same year is made into one observation. The first table represents the base case where we do not make any adjustments or add any criteria.

Base case	-2	-1	0	1	2
Average Prediction error	-0,0092	-0,0101	-0,0058	-0,0100	-0,0086
Median Prediction error	-0,0039	-0,0064	-0,0047	-0,0060	-0,0059
Z-value	-5,60	-5,93	-4,43	-6,85	-6,63

Table 30: displays the average prediction -error and -median, and the Z-values for each year in the event study under the criteria.

The Z-values are heavily negative. The average prediction errors are also negative but rather close to zero, along with the median prediction error. The pattern with highest Z-values are still in year zero similarly to the results from the cross-sectional model. A huge difference from the cross-sectional model is that the average prediction errors tend to follow the patterns that the Z-values have.



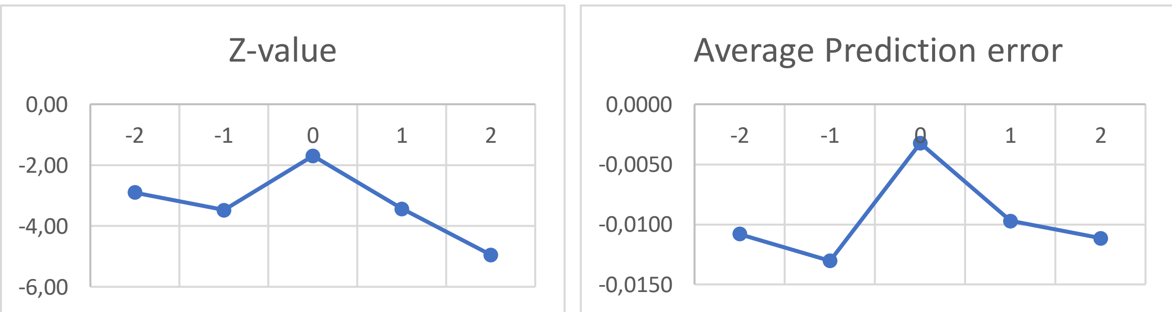
Graph 10:The two graphs display the average prediction error and the Z-values from the base case, calculated the different years in the event study

There seems to be far better evidence of a systematic trend from the decile model. The median values are now much closer to the average compared to the cross-sectional model. As the prediction errors are small, they are best presented using graphs:

The procedure continues like in the cross-sectional model. This time there are only included a single issue from each company. The pattern remains constant with the highest (least negative) Z-values in year zero.

Only one issue	-2	-1	0	1	2
Average Prediction error	-0,0108	-0,0130	-0,0032	-0,0097	-0,0111
Median Prediction error	-0,0016	-0,0032	-0,0019	-0,0037	-0,0047
Z-value	-2,90	-3,48	-1,70	-3,43	-4,95

Table 31: displays the average prediction -error and -median, and the Z-values for each year in the event study from only one issue per company.



Graph 11 The two graphs display the average prediction error and the Z-values calculated the different years in the event study

As the observations decline from the Base case, we get Z-values closer to zero. The average prediction error shows a similar pattern with the highest value also being in year zero. The difference between the event years is bigger than the values from "Base case" but one should be careful to directly compare them, as there could be omitted variables naturally explaining the difference. The average prediction errors do speak in the favor of hypothesis 2.2, but without Z-values with normal values around zero there is no easy way to know how significant these results are.

6.3.2 Decile divided results.

To look at the differences between deciles, the Z-values are divided into the ten deciles. Each company would have maximum of one observation for each year but are included several times if they have issued bonds multiple years.

Decile	-2	-1	0	1	2
10	-6,08	-5,96	-4,66	-5,81	-5,59
9	-1,20	-2,60	-2,78	-3,11	-3,42
8	-1,13	-0,91	-1,39	-2,22	-0,23
7	-1,12	-1,66	-0,26	-1,49	-1,10
6	-0,02	0,70	-2,32	-1,50	-1,49
5	-4,49	-3,49	-1,12	-0,99	-2,48
4	0,43	-0,72	-2,09	-2,03	0,61

Table 32: Displays the Z-values for each decile the different years in the event study.

The pattern with negative results is consistent over all the different deciles, with exceptions of a few places. The results have the biggest negative Z-values in the tenth deciles, likely from having the most observations. The number of observations in each decile is rather quickly reduced and is the probable explanation for the Z-values declining in the lower deciles.

When looking at average prediction errors (table 33) decile ten and seven are the only deciles supporting the general findings in the decile-model.

Decile	-2	-1	0	1	2
10	-0,010	-0,010	-0,008	-0,010	-0,010
9	-0,003	-0,006	-0,005	-0,006	-0,008
8	-0,005	-0,004	-0,008	-0,012	0,001
7	-0,004	-0,011	0,001	-0,008	-0,003
6	0,002	0,002	-0,013	-0,018	-0,020
5	-0,096	-0,056	-0,005	-0,032	-0,080
4	0,074	-0,083	-0,131	-0,159	0,025

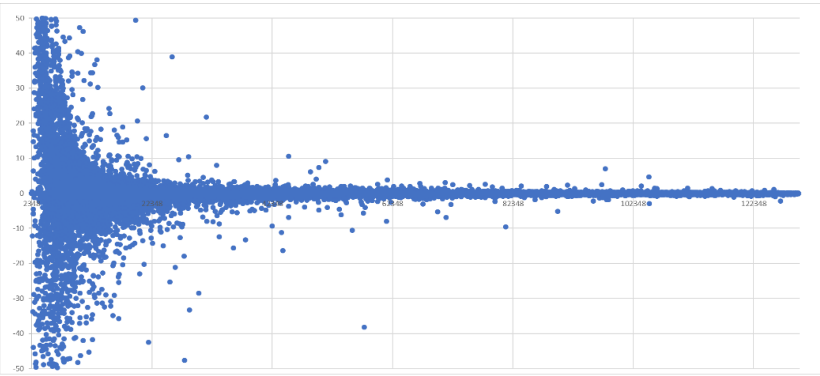
Table 33: Displays the average prediction errors for each decile the different years in the event study

Why these stand out is not clear. As the number of bonds is quickly reduced the results from the lower deciles will have fewer observations and individual deviations will therefore matter more to the average residuals.

6.3.3 Robustness of the decile model

As with the cross-sectional model there are outlier problems in the decile model. A surprise to us is that the residuals fit much better for the companies with the larger asset values than from the cross-sectional model. This is clearly seen when displaying the residuals against the ranked asset value using the same scales in Graph 12 as in graph 9. Graph 12 has 101 236 observations. An interesting point is that number of observations exceeding 50 or blew -50 is only reduced to 1434 in the decile model from 1487 in the cross-sectional model. The new model does little change to the largest outliers in the model found from the companies with the lowest asset value. Looking at the standard deviations for the residuals it goes up, from 200 in the cross-sectional model to 258 in the decile model. This increase is explained through the absolute largest outliers being even bigger than the ones in the cross-sectional model.

In our decile model we excluded decile one, two and three because of lacking bond observations from the smallest deciles. Looking at the residuals with the same criteria drastically changes the standard deviations. The standard deviation of the residuals in the cross-sectional model are then reduced to 16,17 while the same reduction in the decile model reduces the standard deviation to 0,26. It appears that the decile model does not fix the large outliers from companies with the lowest reported asset values, but reduces the residuals a lot for the companies with higher asset values.



Graph 12: Displays the in-sample residuals. The y-axis shows the residual value. The observations are sorted on smallest to biggest asset value and do therefore not display size of total assets in our dataset, but rather the rank from smallest to biggest.

As in the cross-sectional model we tested how the outlier problem affect our residuals. The skew is about the same in this model as in the original model. The kurtosis is relatively reduced from the last model, but still show evidence of a massive fat-tail.

Test	Decile model
Skew	-133
Kurtosis	28804

Table 34: displays the Skew and kurtosis in the decile model. This model includes the entire sample and has not been trimmed by removing the smallest deciles.

As we did not conduct tests for the smallest deciles, we checked the skew and kurtosis statistics without the excluded deciles. We removed the three lowest deciles from the cross-sectional model so the results could be compared.

Test	Cross-sectional	Decile model
Skew	28	-47
Kurtosis	1926	6270

Table 35: Displays the skew and kurtosis number for both the cross-sectional model and the decile model.

The results are improved while still reporting large numbers. The cross-sectional model report better results from the trimmed dataset. From graph 12 and 9, this may be a little surprising, but the explanation is found from the standard deviations. The much bigger standard deviation in the cross-sectional model of 16,17 while decile model reports 0,26 is the explanation of why the kurtosis may be bigger in the decile-model while it looks to be the opposite.

From graph 12 it appears, as in the cross-sectional model, to be problems with heteroskedasticity. We conducted the Whites test and it gave a F-stat of 76. A F-stat of 76 is much better than the cross-sectional result of 1982 but is still a very strong indication of heteroskedasticity.

res_sq	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yhat	-621.3605	223.5033	-2.78	0.005	-1059.424	-183.2969
yhat_2	.1266821	.0111562	11.36	0.000	.1048162	.148548
_cons	61024.62	35621.24	1.71	0.087	-8792.552	130841.8

Table 36: Displays the results from conducting a Whites test. The yhat is the insample predicted values while yhat_2 represent the predicted values squared. They are then regressed on the squared in sample residuals. The test F-stat would then tell us if the regressors have explanatory power on the expected residuals. The test is conducted across the entire dataset and therefore contains residuals and predictions from all the regressions in the decile model.

From the coefficients, big squared residuals are expected from the companies with the lowest (most negative) estimated total accruals. As the estimated total accruals squared are positive, higher estimated accruals would slow the decline in expected squared residuals, and possible start to increase the expected squared residuals with higher estimations. From deriving the whites test the expected low point should be when the estimated total accruals are 4707. As this number is high it is expected that the heteroskedasticity declines from higher predicted values.

6.3.4 General discussion

We had hoped dividing the results differently would grant results giving Z-values closer to zero. If this was the case we could, as (Jones, 1991) did, use the Z-values to tell us about significant differences when issuing bonds. Compared to the cross-sectional model the decile model gives Z-values further from zero and they are in almost all cases heavily negative. The model did give us average prediction errors that are much closer to zero and the median than in the cross-sectional model. There are therefore advantages and disadvantages using the decile model.

The negative values are interesting and leaves the question as to why there are such a huge difference between companies issuing bonds and those who do not, when sorted by size. The results from the cross-sectional model indicated that the larger the issue year was, the larger the Z-values across all event-study years seems to be. It is therefore interesting that the connection seems to be complete opposite when running the regressions, grouped by size rather than industry. The reason why might be found in literature showing that companies with tangible assets often have a higher leverage (Frank & Goyal, 2009). If a lot of the issuers have tangible assets, depreciation of tangible assets may explain the negative difference through EBIX and CFO. Depreciation may cause lower earnings compared to the cash flow from operations. The variable PPE should account for depreciation effect, but there could be differences between the companies issuing bonds and those who don't.

Because of the negative Z-values we cannot confirm any of the earnings management hypothesizes using these results, as it breaks one of the assumptions of expected V-values at zero. The Z-values only tell us that the prediction errors are closer to the normal levels from the in-sample values in year zero. An interesting find is that the average prediction errors seems to be moving together with the highest (closest to zero) Z-values and are always found in year zero. As the overall results are very negative but increase in event year, the results do not speak directly against earnings management. Being able to directly compare the averages could prove if the averages are significantly higher in year zero. We therefore end up with the same problem that we faced in the cross-sectional model. That without the correlations of the error-terms we can't check if there are any significant results.

6.4 Panel regression

As mentioned, a weakness with the Jones model is the assumption of zero covariances when creating the Z-values. This assumption makes it conveniently easier to add up the standardized prediction errors together, without making any adjustments for covariance. The assumption made it possible to create filters in excel to quickly investigate a wide set of scenarios.

A panel regression offers a solution to get the variance-covariance matrix and a common standard error necessary to directly compare the means to each-other. It is however a time-consuming, and extremely data demanding process, and therefore severely limits the possibilities to conduct several tests as we in the decile- and cross-sectional models.

A weakness of the panel data approach compared to the cross-sectional and decile model is the effect of outliers and missing/nonsensical reported values have on the overall results. In the cross-sectional and decile model these issues will have less of an effect because the data problems would be spread on more regressions, causing only a few industry-years to have huge errors. In the panel approach, all observation with data problems will increase the standard error of the regression. To reduce this problem, we removed industries with many omitted observations in the cross-sectional model. We removed industries number 7, 10, 19, 27, 28 and 31.

After running the regression, we found that we didn't omit enough "bad" data. We removed the observation with the 2,5 % of the highest and lowest (most negative) prediction errors. These omitted observations were mainly due to nonsensical values in one of the variables, for example $\left(\frac{1}{A_{it-1}}\right)$ equal to one.

6.4.1 Empirical methodology

We started off with the cross-sectional regression (equation 3.7), then added a dummy variable for each industry-year. This means that the regression contains 3 844 regressors. The prediction error is defined as:

$$u_{it} = y - \hat{y} \tag{6.2}$$

More precisely:

$$u_{it} = \left(\frac{TA_{it}}{A_{it-1}}\right) - D_{1990,j} * \left[\alpha_t \left(\frac{1}{A_{it-1}}\right) + \beta_{1t}\left(\frac{\Delta REV_{it}}{A_{it-1}}\right) + \beta_{2t}\left(\frac{PPE_{it}}{A_{it-1}}\right)\right]$$
$$\dots - D_{T,J} * \left[\alpha_t \left(\frac{1}{A_{it-1}}\right) + \beta_{1t}\left(\frac{\Delta REV_{it}}{A_{it-1}}\right) + \beta_{2t}\left(\frac{PPE_{it}}{A_{it-1}}\right)\right] \quad (6.3)$$

u_{it} is the prediction error for a given company in a given year. Subscript i is a specific company, J is the industry that the company operates in, t is time and D is the dummy variable with subscripts for year and industry, the value equals one for the year and industry which the observation is from.

The sum of prediction errors:

$$C = \sum_{i=1}^{n_0} u_{it} \quad (6.4)$$

Further the variance-covariance matrix of the prediction error is defined as:

$$V(u_{it}) = SE^2 I + X_0 V(b) X_0' \quad (6.5)$$

$$V(u_{it}) = SE^2 I + SE^2 X_0 (X'X)^{-1} X_0' \quad (6.6)$$

where I is the identity matrix, SE is the standard error of the regression

The variance of the summarized prediction error is:

$$V(c) = 1' V(u_{it}) 1 \quad (6.7)$$

X refers to the in-sample companies and X_0 refers to out of sample companies, all variables with subscript 0 is an out-of-sample variable. In the cross-sectional model the matrix $(X'X)^{-1}$ and the SE are different for each regression, creating difficulties when calculating the variance of the summarized prediction error ($V(c)$). The reason we try the panel data approach is that we want to create a regression in which the $(X'X)^{-1}$ matrix and the SE^2 are constant when making the predictions. We can then use the sum or average prediction error to create comparable results to check whether the results from each year differs from each other.

The average prediction error is better suited with the possibility to compare the years to each other. This is because the summarized prediction error will be heavily influenced by the number of observation that year.

The average prediction error:

$$\bar{c} = \frac{1}{n_0}\sum_{i=1}^{n_0} u_{it} \tag{6.8}$$

Standard error of average prediction error

$$SE(\bar{c}) = \frac{V(c)}{n_0} \tag{6.9}$$

$$\mathrm{T-value} = \frac{\bar{c}}{SE(\bar{c})} \tag{6.10}$$

A problem with creating the $V(b)$ from equation 6.5, is that the data size of the $V(b)$ increases exponentially for each industry-year. We therefore keep the assumption of no correlation between the X-variables between the industries and no autocorrelation between the years. The V(b) will therefore be the same for each industry-year, but with a SE for the entire dataset. Further the covariance of the standard deviation of the prediction error within an industry-year will be included in the $V(c)$. The panel data calculations would implicit become a robustness test, as we get the covariance of the SDPE within an industry-year. Low covariance would mean that our assumptions of no covariances between the error terms would not be too outrageous.

	Year -2	Year -1	Year 0	Year 1	Year 2
T-values	0,0127	0,0040	0,0160	0,0191	-0,0004
C	12,33	3,97	14,59	16,77	-0,35
Var	897,99	914,21	875,37	943,26	815,78
cov	70,66	88,51	37,07	-64,52	73,90
V(c)	968,65	1002,72	912,44	878,74	889,68
n	753	749	754	732	690
Average C	0,016	0,005	0,019	0,023	-0,0005

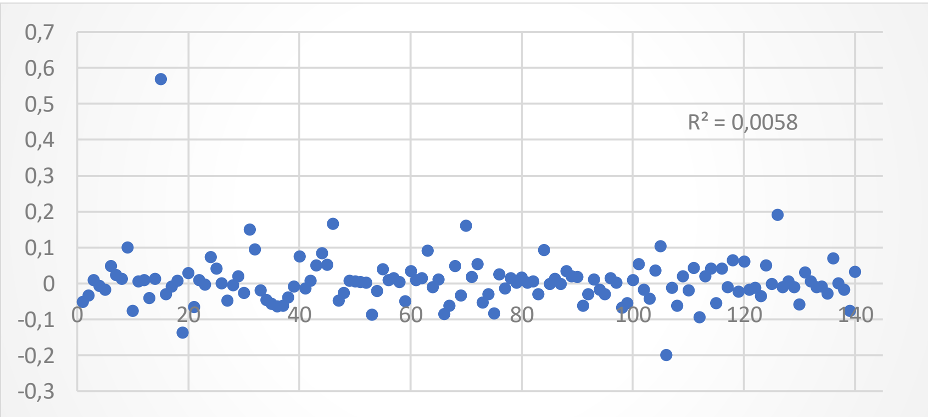
Table 37: Average C is the average prediction error, n is out of sample observations, V(c) is the sum of variances and covariances, Var is sum if variances, Cov is the sum of covariances, C is total prediction errors.

None of the years are close to being significant from zero, but the pattern of the average prediction error is interesting. As expected, the average prediction error is higher in year zero than the years prior, however they are higher in year 1 than zero. We don't have a theoretical explanation or economical reasoning for this, which indicates that the deviations are caused by the large variances and covariances.

6.5 Risk-shift and earnings management

We found evidence that gave some support to our risk-shifting hypothesis, however we weren't able to conclude with any certainty whether companies engage in earnings management. Due to the pattern of the highest average prediction errors occurring in year zero, we decided to investigate whether there is a relation between earnings management and risk-shifting. Our intuition is that there might be companies that engage in earnings management, but overall, we can't find significant evidence of companies systematically engaging in earning management when issuing debt. Our hypothesis is that companies which have increased volatility after issue is more likely to engage in earnings management prior to issue.

After looking at several ways of grouping companies with increased volatility after issue and companies with high prediction errors in issue year, we concluded that there didn't seem to be a relation between risk-shift and earnings management.



Graph 13 Horizontal axis is companies with significantly higher volatility in year 1 than year zero and sorted on rank from low to high significance. Prediction errors from decile model on vertical axis.

There seems to be little correlation between having a higher significance and having high prediction errors, a low R^2 also indicates no relation. This is one arbitrary example of different ways we looked at risk-shift and earnings management, and none of them gave an indication of a relation. Graph 13 includes only significantly higher volatilities in year 1. We have looked at whether there is a difference in earnings management from companies with both insignificant volatility change and companies with significant volatility change. As mentioned, the graph is an arbitrary choice of many graphs yielding the same result.

7 Conclusion

In this thesis we have tried to answer the question of whether companies engage in earnings management prior to issue of debt, and if their asset volatility increases after. We tried to answer our main hypothesis through answering several sub-hypothesizes.

The risk-shifting analysis gave evidence to support our hypothesis of increased volatility after issue of debt. The average volatility in our data proved to give a huge jump after issuing. The Merton-model is a theoretical model and we must make a lot of assumptions in order to conduct the calculation. There is a possibility that the results are produced through a mechanical error that occurs after debt issue. A factor that may have caused us to get such a high increase is the assumptions of 10-year average maturity on long term debt.

Levenes test showed us that a lot of companies had significantly higher volatility one year after debt issue. We weren't able to significance test whether this increase in number of companies was significantly higher. There seemed to be indications that the companies with highest leverage also are the ones risk-shifting, but again we didn't have a significance test to conclude.

Conducting the earnings management tests proved to be a bit of a challenge. From the cross-sectional Jones model we got Z-values which had the pattern we expected. However, after further investigation we found that the average and median prediction errors didn't follow this pattern. The average and median prediction error also indicated a model with a poor fit to find the non-discretionary accruals. The idea of the Jones model is to establish a "normal" value and look for systematic deviations from this level. The problem is when we have two different datasets distinguished by issuing bonds or not, there may be correlation between total accruals and the companies issuing bonds. If the Z-values had been more stable around zero except when issuing bonds, we could use the Z-value as proof of earnings management. The Z-values being more random indicates that we have failed to create a model that correctly calculates the normal values. Without Z-values around a normal level we need to see if the average prediction errors are significantly different from each other. To do this we need to know the correlations for the error-terms. In other words, Jones' simplifications create problems when trying to directly compare the different years to each-other.

To cope with the cross-sectional model providing a bad fit, we grouped the companies in deciles. The decile model, especially after the removal of the lowest deciles proved to be more reliable to find sensical average prediction errors, but the Z-values had a negative deviation from zero making significant testing difficult. We did find an interesting pattern in our decile model, but without the possibility to significant test the averages we must use the Z-values, and we had no basis to conclude on the Z-values

With the panel data we hoped to fix the correlation issue in order to conduct proper significant tests to see if there were significant differences. Because we used the cross-sectional model as the basis we transferred the outlier problem into the panel regression creating huge variances. The variances became so big calculating any significant tests other than the deviation from zero proved to be pointless.

The cross-sectional model proved to be a bad fit, with opposing Z-values and average prediction errors. The decile model yielded negative Z-values which meant no significantly higher discretionary accruals. The panel data model had outlier problems which gave t-values of almost zero. Because of this we reject all our hypothesizes from earnings management.

On the basis of our tests we believe that managers might engage in dis-honest strategies when issuing debt, but further investigation is needed to properly check and significance test our findings.

7.1 Experiences from this thesis for further analyses

Finding a good model to create accurate predictions proved to be difficult. There were different problems with each model. Using the industry-classification did not prove to be accurate enough giving prediction errors to often deviating far from zero. The decile model proved better at finding reasonable prediction errors, but there proved to be negative correlations between total accruals and companies issuing debt causing negative averages and Z-values. The panel data proved practically difficult and time consuming to conduct, but nonetheless gave us the correlations we were looking for. The panel method works but gave us the same outlier problem we faced in the cross-sectional model. Our recommendations for further analysis is therefor, conduct the panel data approach at the trimmed decile model.

We chose to use a large dataset having over 100 000 observations in the prediction models, to get enough observations to conduct the tests across so many industries and years. A problem with a dataset at this size is that it creates difficulties in checking if the data material is correct or not. A lot of the companies reported numbers that are difficult to interpret. A smaller dataset would make it easier to more thoroughly check the data.

The risk shifting proved to give us better results, but one may be skeptical. The calculated volatilities are high and there are several factors that may have influenced our results. As our robustness using the 1-year model proved to give the opposite results it could be that we do not correctly implement the maturity correctly. Further analysis may try different methods in calculating the time to maturity to see if there exist a better way to get a good average time to maturity. One way may be to try a different long-term debt average in equation (2.17) or a way to calculate them for each individually company.

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Appendix 1 - Data sampling steps in DataStream:

Equities: steps in request table (Excel add-in)

1. Clear all
2. Equities
3. US market & US Dollar
4. Only equities (exclude preferred shares etc)
5. Exclude banks and financial service
6. Base date = 2013
7. Need to be RIC linked
8. Security: major

This yielded 11 701 equities.

After retrieving the equities, we used the request table to get company ISIN (ISIN), Ticker (WC05601), SIC code (WC07021) and name (WC06001). Then removed equities without ISIN and SIC code, leaving 9499 companies.

BONDS: collected from Eikon interface

1. Bonds and notes
2. Issuer type: Corporate
3. US market & US Dollar
4. Exclude year 2020
5. Exclude banks & financial service sector.
6. Exclude Bonds without ISIN

We were able to extract 11 413 bonds.

<u>Matching bonds with companies</u>:

The benefit of retrieving bond information from Eikon`s interface rather than the excel add-in is the additional information one gets, such as issuers ticker and name. We matched bonds and companies through company name, ticker and cusip.

N	O	P	Q	V	W	X
Company ISIN	VLOOKUP Ticker	VLOOKUP name	VLOOKUP CUSIP	Control	Control	control
US00751Y1064	#I/T	US00751Y1064	US00751Y1064	#I/T	#I/T	Right
US00751Y1064	#I/T	US00751Y1064	US00751Y1064	#I/T	#I/T	Right
US0378331005	#I/T	US0378331005	US0378331005	#I/T	#I/T	Right
US0378331005	#I/T	US0378331005	US0378331005	#I/T	#I/T	Right
US8843151023	#I/T	#I/T	US8843151023	#I/T	#I/T	#I/T
US00287Y1091	US00287Y1091	US00287Y1091	US00287Y1091	Right	Right	Right
US00287Y1091	US00287Y1091	US00287Y1091	US00287Y1091	Right	Right	Right
US00287Y1091	US00287Y1091	US00287Y1091	US00287Y1091	Right	Right	Right
US00287Y1091	US00287Y1091	US00287Y1091	US00287Y1091	Right	Right	Right
US03073E1055	#I/T	US03073E1055	US03073E1055	#I/T	#I/T	Right
US0007521059	#I/T	#I/T	US0007521059	#I/T	#I/T	#I/T
US0007521059	#I/T	#I/T	US0007521059	#I/T	#I/T	#I/T
US0028241000	US0028241000	US0028241000	US0028241000	Right	Right	Right
US0028241000	US0028241000	US0028241000	US0028241000	Right	Right	Right
US0028241000	US0028241000	US0028241000	#I/T	Right	#I/T	#I/T
US7908491035	#I/T	#I/T	US7908491035	#I/T	#I/T	#I/T
US0326541051	#I/T	US0326541051	US0326541051	#I/T	#I/T	Right
US0394831020	#I/T	US0394831020	US0394831020	#I/T	#I/T	Right
US0527691069	#I/T	US0527691069	US0527691069	#I/T	#I/T	Right

In columns O to Q we Matched bonds with companies by using VLOOKUP. Column "N" is computed with a formula that tells excel to insert ISIN from column "Q", if there are no ISIN it checks column "O" if there is no ISIN there either it looks in column "P". Columns V, W and X were used to control for the possibility of ticker, cusip and name giving different ISIN`s.  After correcting for different ISIN`s being produced from the three methods, we were able to extract 5 272 matches.

Appendix 2: R^2 calculations for Cross-Sectional and Decile model

	Cross Sectional model																														
	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1		41 %	36 %	15 %	27 %	17 %	6 %	13 %	51 %	81 %	100 %	87 %	99 %	92 %	4 %	40 %	92 %	43 %	98 %	65 %	60 %	27 %	94 %	56 %	87 %	84 %	7 %	8 %	0 %	14 %	77 %
2		50 %	65 %	34 %	29 %	20 %	69 %	21 %	100 %	94 %	100 %	99 %	75 %	100 %	51 %	23 %	41 %	24 %	97 %	29 %	32 %	8 %	2 %	38 %	24 %	33 %	59 %	29 %	9 %	72 %	6 %
3		87 %	33 %	62 %	69 %	71 %	62 %	42 %	40 %	100 %	96 %	11 %	39 %	65 %	99 %	100 %	80 %	53 %	98 %	44 %	54 %	29 %	72 %	100 %	99 %	99 %	100 %	44 %	59 %	36 %	36 %
4		34 %	23 %	44 %	21 %	22 %	20 %	22 %	22 %	36 %	100 %	99 %	100 %	14 %	77 %	52 %	6 %	100 %	86 %	10 %	39 %	10 %	93 %	9 %	48 %	100 %	46 %	48 %	100 %	100 %	13 %
5		72 %	86 %	67 %	55 %	71 %	33 %	57 %	8 %	30 %	94 %	73 %	54 %	73 %	19 %	33 %	76 %	45 %	70 %	20 %	6 %	100 %	100 %	72 %	100 %	70 %	23 %	53 %	7 %	23 %	2 %
6		30 %	63 %	43 %	33 %	12 %	98 %	5 %	100 %	98 %	3 %	36 %	29 %	86 %	65 %	30 %	17 %	86 %	97 %	87 %	54 %	63 %	83 %	3 %	44 %	34 %	27 %	82 %	99 %	49 %	61 %
7																															
8		21 %	32 %	100 %	39 %	5 %	96 %	100 %	17 %	41 %	17 %	31 %	1 %	21 %	18 %	15 %	60 %	26 %	49 %	45 %	22 %	6 %	27 %	14 %	39 %	38 %	73 %	94 %	90 %	49 %	1 %
9		48 %	55 %	24 %	40 %	43 %	37 %	27 %	31 %	93 %	77 %	98 %	79 %	84 %	83 %	76 %	39 %	96 %	11 %	100 %	99 %	1 %	41 %	100 %	97 %	90 %	31 %	62 %	97 %	49 %	77 %
10											23 %	10 %	88 %	80 %	100 %	63 %	60 %	83 %	98 %	100 %	98 %	100 %	91 %	37 %	100 %	30 %	46 %				
11		36 %	22 %	41 %	20 %	77 %	19 %	29 %	100 %	80 %	70 %	73 %	87 %	65 %	14 %	42 %	54 %	33 %	29 %	19 %	8 %	13 %	23 %	3 %	27 %	46 %	99 %	12 %	19 %	25 %	29 %
12		55 %	71 %	77 %	34 %	65 %	27 %	34 %	9 %	10 %	77 %	30 %	91 %	100 %	84 %	95 %	12 %	82 %	65 %	86 %	92 %	74 %	96 %	38 %	7 %	12 %	57 %	100 %	0 %	3 %	80 %
13		15 %	5 %	9 %	9 %	1 %	8 %	4 %	10 %	100 %	78 %	4 %	3 %	99 %	18 %	38 %	13 %	18 %	4 %	31 %	18 %	23 %	90 %	30 %	99 %	45 %	24 %	95 %	37 %	9 %	17 %
14		43 %	54 %	53 %	72 %	72 %	37 %	83 %	86 %	63 %	21 %	52 %	22 %	100 %	97 %	76 %	85 %	9 %	95 %	100 %	100 %	71 %	5 %	100 %	70 %	86 %	100 %	65 %	92 %	100 %	74 %
15		67 %	64 %	69 %	56 %	66 %	99 %	83 %	36 %	37 %	89 %	100 %	93 %	53 %	92 %	22 %	99 %	100 %	46 %	19 %	11 %	98 %	20 %	98 %	76 %	91 %	12 %	54 %	32 %	91 %	100 %
16		25 %	36 %	40 %	21 %	26 %	17 %	15 %	24 %	10 %	91 %	65 %	85 %	95 %	80 %	88 %	45 %	100 %	31 %	91 %	86 %	24 %	18 %	100 %	15 %	100 %	100 %	99 %	43 %	11 %	26 %
17		90 %	66 %	54 %	88 %	13 %	19 %	53 %	34 %	13 %	1 %	34 %	54 %	97 %	44 %	48 %	100 %	33 %	34 %	82 %	99 %	70 %	89 %	17 %	89 %	94 %	41 %	58 %	95 %	75 %	45 %
18		44 %	42 %	76 %	74 %	58 %	54 %	30 %	57 %	32 %	68 %	73 %	73 %	100 %	100 %	93 %	100 %	93 %	53 %	78 %	98 %	91 %	59 %	51 %	100 %	20 %	52 %	64 %	93 %	97 %	100 %
19								33 %	78 %	37 %	86 %	100 %	96 %	88 %	65 %	99 %	94 %	58 %	12 %	52 %	76 %	98 %	98 %	1 %	100 %	97 %					
20		84 %	73 %	66 %	38 %	50 %	34 %	87 %	66 %	65 %	53 %	33 %	49 %	99 %	99 %	96 %	100 %	100 %	100 %	51 %	80 %	100 %	94 %	98 %	59 %	62 %	44 %	17 %	80 %	76 %	87 %
21		31 %	79 %	62 %	60 %	31 %	45 %	5 %	7 %	100 %	62 %	11 %	100 %	80 %	99 %	21 %	100 %	100 %	99 %	6 %	27 %	14 %	70 %	93 %	71 %	48 %	39 %	65 %	22 %	10 %	67 %
22		41 %	40 %	37 %	28 %	97 %	93 %	51 %	96 %	9 %	3 %	27 %	67 %	84 %	78 %	38 %	62 %	99 %	97 %	99 %	42 %	83 %	89 %	100 %	10 %	23 %	0 %	16 %	90 %	21 %	100 %
23		58 %	74 %	45 %	51 %	52 %	31 %	63 %	33 %	30 %	89 %	30 %	90 %	100 %	16 %	1 %	33 %	6 %	21 %	24 %	96 %	80 %	73 %	42 %	26 %	12 %	48 %	61 %	47 %	27 %	29 %
24		72 %	50 %	75 %	74 %	62 %	72 %	73 %	56 %	82 %	100 %	15 %	12 %	95 %	100 %	37 %	69 %	100 %	19 %	12 %	2 %	13 %	29 %	88 %	96 %	97 %	25 %	100 %	100 %	64 %	71 %
25		61 %	60 %	30 %	56 %	36 %	16 %	32 %	14 %	27 %	13 %	92 %	98 %	100 %	100 %	75 %	10 %	54 %	11 %	81 %	84 %	9 %	18 %	28 %	96 %	66 %	98 %	99 %	100 %	73 %	91 %
26				56 %	35 %	34 %	84 %	18 %	55 %	54 %	29 %	9 %	86 %	92 %	75 %	6 %	47 %	5 %	94 %	17 %	25 %	59 %	12 %	0 %	76 %	88 %	20 %	2 %	99 %	11 %	38 %
27					72 %	51 %	38 %	38 %	78 %	81 %	81 %	97 %	52 %	100 %	100 %	100 %	99 %	84 %	100 %	68 %	67 %	100 %	45 %	42 %	25 %	100 %					
28														70 %	72 %	83 %	84 %	56 %	100 %	97 %	98 %	35 %	100 %	34 %	100 %	97 %					
29		82 %	83 %	77 %	32 %	65 %	48 %	69 %	55 %	66 %	47 %	28 %	75 %	48 %	33 %	96 %	100 %	7 %	97 %	91 %	98 %	74 %	52 %	100 %	100 %	57 %	52 %	59 %	97 %	59 %	61 %
30		33 %	27 %	26 %	38 %	79 %	59 %	16 %	36 %	52 %	5 %	15 %	93 %	98 %	64 %	94 %	72 %	5 %	99 %	100 %	100 %	99 %	54 %	99 %	34 %	99 %	100 %	66 %	59 %	94 %	36 %
31		32 %	64 %	24 %	13 %	37 %	39 %	12 %	14 %	100 %	44 %	25 %	24 %	93 %	6 %	27 %	79 %	76 %	67 %	100 %	62 %	77 %	91 %	76 %	71 %	76 %	95 %	16 %	80 %	99 %	100 %

Table 38: displays the R^2 numbers from the cross sectional regressions. Numbers are rounded to nearest %. (No R^2 numbers are 100%)

	Decile model																													
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Decile	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1	19 %	37 %	100 %	24 %	47 %	78 %	100 %	99 %	37 %	22 %	32 %	13 %	19 %	18 %	5 %	26 %	57 %	5 %	1 %	2 %	80 %	89 %	15 %	41 %	16 %	23 %	84 %	43 %	14 %	77 %
2	25 %	11 %	11 %	12 %	5 %	14 %	12 %	25 %	8 %	3 %	25 %	18 %	13 %	11 %	9 %	17 %	13 %	9 %	7 %	72 %	12 %	5 %	15 %	89 %	6 %	15 %	14 %	10 %	6 %	31 %
3	39 %	38 %	26 %	16 %	8 %	11 %	12 %	12 %	9 %	17 %	14 %	20 %	23 %	9 %	13 %	16 %	3 %	7 %	4 %	2 %	3 %	15 %	19 %	17 %	14 %	20 %	31 %	9 %	10 %	12 %
4	42 %	34 %	30 %	21 %	31 %	11 %	18 %	10 %	11 %	16 %	9 %	25 %	22 %	8 %	8 %	10 %	12 %	10 %	4 %	15 %	54 %	8 %	5 %	10 %	34 %	23 %	6 %	7 %	11 %	20 %
5	26 %	20 %	31 %	21 %	27 %	19 %	18 %	12 %	13 %	9 %	6 %	19 %	9 %	22 %	6 %	9 %	13 %	10 %	16 %	15 %	15 %	2 %	12 %	21 %	16 %	31 %	23 %	23 %	39 %	35 %
6	46 %	48 %	37 %	49 %	23 %	25 %	19 %	19 %	21 %	29 %	2 %	32 %	22 %	27 %	43 %	12 %	12 %	21 %	28 %	31 %	14 %	14 %	18 %	39 %	25 %	32 %	26 %	31 %	29 %	47 %
7	43 %	46 %	42 %	38 %	42 %	17 %	28 %	23 %	28 %	11 %	6 %	18 %	28 %	29 %	19 %	14 %	15 %	22 %	31 %	41 %	21 %	20 %	33 %	28 %	8 %	33 %	47 %	24 %	36 %	48 %
8	43 %	45 %	43 %	47 %	38 %	31 %	34 %	21 %	40 %	31 %	4 %	33 %	23 %	39 %	27 %	30 %	30 %	38 %	35 %	39 %	34 %	23 %	30 %	42 %	40 %	37 %	41 %	42 %	39 %	46 %
9	55 %	64 %	65 %	53 %	58 %	47 %	37 %	39 %	39 %	29 %	15 %	26 %	44 %	15 %	30 %	3 %	18 %	31 %	24 %	9 %	18 %	41 %	38 %	34 %	36 %	39 %	49 %	45 %	41 %	38 %
10	58 %	68 %	67 %	61 %	66 %	53 %	54 %	44 %	36 %	35 %	27 %	20 %	36 %	41 %	44 %	29 %	15 %	33 %	33 %	39 %	34 %	29 %	29 %	46 %	38 %	47 %	42 %	46 %	41 %	44 %

Table 39: Displays the R^2 numbers for the Decile-model. Rounded to nearest %

Appendix 3: Datatype definition by Datastream

Income From Continuing Operations - WC18150

Supplementary (Income) Data, Annual & Interim Item; Field 18150

All Industries:

INCOME FROM CONTINUING OPERATIONS represents the amount earned by a company before any adjustment for preferred dividends, discontinued operations and extraordinary items. Data for this field is generally not available prior to 1996 for non-U.S. companies and 1991 for U.S. companies.

http://product.datastream.com/Navigator/HelpFiles/DatatypeDefinitions/en/0/WC18150.htm

Net Cash Flow - Operating Activities - WC04860

Cash Flow Data, Annual & Interim Item; Field 04860

All Industries:

NET CASH FLOW - OPERATING ACTIVITIES represent the net cash receipts and disbursements resulting from the operations of the company. It is the sum of Funds from Operations, Funds From/Used for Other Operating Activities and Extraordinary Items.

Data for this field is generally not available prior to 1989.

It includes but is not restricted to:

Funds from operations

Funds from/for working capital

Extraordinary items

http://product.datastream.com/Navigator/HelpFiles/DatatypeDefinitions/en/0/WC04860.htm

Total Assets - WC02999

Asset Data, Annual & Interim Item; Field 02999

All Industries:

TOTAL ASSETS represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.

Banks:

TOTAL ASSETS represent the sum of cash & due from banks, total investments, net loans, customer liability on acceptances (if included in total assets), investment in unconsolidated subsidiaries, real estate assets, net property, plant and equipment and other assets.

Insurance Companies:

TOTAL ASSETS represent the sum of cash, total investments, premium balance receivables, investments in unconsolidated subsidiaries, net property, plant and equipment and other assets.

Other Financial Companies:

TOTAL ASSETS represent the sum of cash & equivalents, receivables, securities inventory, custody securities, total investments, net loans, net property, plant and equipment, investments in unconsolidated subsidiaries and other assets.

http://product.datastream.com/Navigator/HelpFiles/DatatypeDefinitions/en/0/WC02999.htm

Property, Plant And Equipment – Gross WC02301

Asset Data, Annual & Interim Item; Field 02301

Industrials, Other Financial Companies:

PROPERTY, PLANT AND EQUIPMENT (GROSS) represents tangible assets with an expected useful life of over one year which are expected to be used to produce goods for sale or for distribution of services.

It includes but is not restricted to:

Land

Buildings

Machinery

Equipment

Construction work in progress

Minerals

Oil

Autos & trucks

Timberland and timber rights

Leasehold improvements

Rented equipment, if depreciated

Furniture and fixtures

Property, Plant and Equipment leased under capitalized lease obligations

Book plates

Non-current film costs and inventory

Broadcasting rights and licenses

Franchise rights and licenses

Publishing rights and licenses

Funds held for construction

Long term power purchase contacts

Software products

It excludes:

Tools and dies amortized over less than two years

Excess carrying value over cost of property

Copyrights, trademarks, patents and goodwill

Property not used in operations or used in operations to be discontinued

Property held for sale for companies other than Real Estate (treated as investment and advances)

http://product.datastream.com/Navigator/HelpFiles/DatatypeDefinitions/en/0/WC02301.htm

Net Sales Or Revenues - WC01001

Income Data, Annual & Interim Item; Field 01001

Industrials :

NET SALES OR REVENUES represent gross sales and other operating revenue less discounts, returns and allowances.

It includes but is not restricted to:

- Franchise sales when corresponding costs are available and included in expenses.
- Consulting fees
- Service income
- Royalty income when included in revenues by the company.
- Contracts-in-progress income
- Licensing and franchise fees
- Income derived from equipment lease or rental when considered part of operating revenue
- Commissions earned (not gross billings) for advertising companies
- Income from leased departments

It excludes:

- Non-operating income
- Interest income
- Interest capitalized
- Equity in earnings of unconsolidated subsidiaries
- Rental income
- Dividend income
- Foreign exchange adjustment
- Gain on debt retired
- Sale of land or natural resources
- Sale of plant and equipment
- Sale of investment
- Sales from discontinued operations
- Security transactions
- Income on reserve fund securities when shown separately
- Operating differential subsidies for shipping companies

Net mutual aid assistance for airlines companies

General and Service Taxes

Value-Added taxes

Excise taxes

Windfall Profit Taxes

Banks, Insurance and Other Financial Companies:

REVENUES represent the total operating revenue of the company.

It includes but is not restricted to:

For Banks:

Interest and fees on loans

Interest on Federal Funds

Interest on Bank Deposits

Interest on State, County and Municipality Funds

Interest on U.S. Government and Federal Agencies Securities

Federal Funds sold and securities purchased under resale agreements

Lease Financing

Net leasing revenue

Income from Trading Accounts

Foreign Exchange Income

Investment Securities gains/losses

Service Charges on Deposits

Other Service Fees

Trust Income

Commissions and Fees

For Insurance Companies:

Premiums Earned

Investment income (if the company reports this item net of expenses then the net amount is shown after excluding interest expense)

Other operating income

Gains/Losses on sale of securities (pre-tax)

For Other Financial Companies:

Investment income/loss

Interest income

Income from trading accounts

Trust income

Commission and fees

Rental Income

Securities purchased under resale agreements

Investment Banking income

Principal Transactions

http://product.datastream.com/Navigator/HelpFiles/DatatypeDefinitions/en/0/WC01001.htm

Total liabilities – WC03351A

Liability Data, Annual & Interim Item; Field 03351

All Industries:

TOTAL LIABILITIES represent all short and long term obligations expected to be satisfied by the company.

It includes but is not restricted to:

Current Liabilities

Long Term Debt

Provision for Risk and Charges (non-U.S. corporations)

Deferred taxes

Deferred income

Other liabilities

Deferred tax liability in untaxed reserves (non-U.S. corporations)

Unrealized gain/loss on marketable securities (insurance companies)

Pension/Post retirement benefits

Securities purchased under resale agreements (banks)

It excludes:

Minority Interest

Preferred stock equity

Common stock equity

Non-equity reserves

Current liabilities – WC03101A

Liability Data, Annual & Interim Item; Field 03101

Industrials:

CURRENT LIABILITIES - TOTAL represent debt or other obligations that the company expects to satisfy within one year.

It includes but is not restricted to:

Accounts payable

Short term debt

Notes payable

Current portion of long term debt

All accrued expenses

Other current liabilities

Income taxes payable

Dividends payable

State franchise taxes

Deferred credits

Negative inventories (non-U.S. corporations)

Obligations expected to be satisfied within four years (Germany)

Footnotes:

B. Company does not report current liabilities; calculated

G. No standard text

Ongoing update discontinued from Oct 2012

A. Includes liabilities due in four years or less for Germany

C. May include some long term debt

F. Includes liabilities due in four years or less, may also include some long term debt

O. Adjusted to include accrued expenses

Dividend – WC04551A

Cash Flow Data, Annual & Interim Item; Field 04551

All Industries:

CASH DIVIDENDS PAID - TOTAL represent the total common and preferred dividends paid to shareholders of the company.

It excludes:

Dividends paid to minority shareholders

Footnotes:

A. Included in other sources or uses

Ongoing update discontinued from Oct 2012

B. Includes bonuses to directors

C. Prior year's proposed dividend

Interest expense – WC01251A

Expense Data, Annual & Interim Item; Field 01251

All Industries:

INTEREST EXPENSE ON DEBT represents the service charge for the use of capital before the reduction for interest capitalized. If interest expense is reported net of interest income, and interest income cannot be found the net figure is shown.

It includes but is not restricted to:

Interest expense on short term debt

Interest expense on long term debt and capitalized lease obligations

Amortization expense associated with the issuance of debt

Similar charges

Footnotes:

A. Net expense

B. Similar charges are included

D. Net interest expense and similar charges may be included

Ongoing update discontinued from Oct 2012

C. Other financial charges may be included

J. Includes other income or expense

L. Includes income taxes

Risk-free rate – FRTC1Y

Interest Rates - United States Treasury Constant Maturity, Nominal

Yields on Treasury nominal securities at “constant maturity” are interpolated by the U.S. Treasury from the daily yield curve for non-inflation-indexed Treasury securities. This curve, which relates the yield on a security to its time to maturity, is based on the closing market bid yields on actively traded Treasury securities in the over-the-counter market. These market yields are calculated from composites of quotations obtained by the Federal Reserve Bank of New York. The constant maturity yield values are read from the yield curve at fixed maturities, currently 1, 3, and 6 months and 1, 2, 3, 5, 7, 10, 20, and 30 years.