Aalto University
School of Business

Fundamental risk and profitability: Evidence from high-tech companies

Accounting

Master's thesis

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2013

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Abstract of master's thesis

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Title of thesis	Fundamental risk and profitability: Evidence from high-tech companies
Degree	Master's degree
Degree programme	Accounting
Thesis advisor(s)	Juha Kinnunen, Harri Seppänen
Year of approval 2013	**Number of pages** 79 **Language** English

Abstract

GOAL

The goal of the study is to investigate whether fundamental risk explains future profitability in high-tech firms. Finance theories suggest that there is a positive connection between risk and returns. However, it is also possible that high risk leads to financial distress which can result in lower future profitability. I expect to find a significant association between fundamental risk and future profitability. The direction of the association is hard to predict, as current evidence is mixed.

SAMPLE

The sample used in the empirical tests consists of 14 749 publicly listed high-tech firms from 81 countries. The data was collected from Thomson One Banker database and it covers the years 1990-2010.

RESEARCH METHODS

The main tests were done using binary logistic regression. The dependent variable was a dummy that receives the value 1 when return on assets is zero or larger and 0 otherwise. The independent variables measure profitability, general business risk and financial risk. Two kinds of models were constructed: Parsimonious and Comprehensive. The Parsimonious model uses a narrower selection of independent variables and does not use lagged data. The Comprehensive model uses a wider range of risk proxies. Robustness tests were done using both ordinal logistic regression and multinomial logistic regression.

MAIN RESULTS

The study found that there is a negative association between fundamental risk and future profitability. This implies that financial statement information is useful in explaining future profitability in high-tech firms. Interestingly, high risk seems to lead to lower future profitability, which is in contrast with the risk-return premise in finance. This connection is even stronger in IPO firms which are presumed to be riskier than seasoned firms. It is evident that a model with a few key figures has the 'maximum' explanatory power and the use of a more comprehensive model is not beneficial.

Keywords Fundamental risk, profitability, high-tech firm, regression analysis

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Maisterintutkinnon tutkielman tiivistelmä

Tekijä Topi Peltonen

Työn nimi Riskin ja kannattavuuden yhteys high tech yrityksissä

Tutkinto Kauppatieteiden Maisteri

Koulutusohjelma Laskentatoimi

Työn ohjaaja(t) Juha Kinnunen, Harri Seppänen

Hyväksymisvuosi 2013 **Sivumäärä** 79 **Kieli** Englanti

Tiivistelmä

TAVOITE

Tutkielman tavoitteena on selvittää, selittääkö fundamentaalinen riski tulevaa kannattavuutta high-tech yrityksissä. Rahoitusteorioiden mukaan riskin ja tuottojen välillä on positiivinen yhteys. Kuitenkin korkea riski saattaa vaikeuttaa yritysten mahdollisuuksia täyttää taloudelliset sitoumuksensa, joka voi laskea tulevaa kannattavuutta. Odotan että fundamentaalisen riskin ja kannattavuuden väliltä löytyy vahva tilastollinen yhteys, mutta on vaikea arvioida, onko se positiivinen vai negatiivinen.

AINEISTO

Tutkimuksen aineisto käsittää 14 749 pörssilistattua high-tech yritystä 81 maasta. Aineisto kerättiin Thomson One Banker tietokannasta ja se kattaa vuodet 1990-2010.

MENETELMÄT

Empiirisen osan päätestit suoritettiin binäärisellä logistisella regressiomenetelmällä. Selitettävänä muuttujana oli kategorinen muuttuja, joka saa arvon 1 kun yrityksen koko pääoman tuottoaste on 0 tai suurempi, ja arvon 0 muutoin. Mallin selittävät muuttujat mittaavat kannattavuutta, yleistä yritysriskiä ja rahoitusriskiä. Tutkimuksessa muodostettiin ensin yksinkertaisempi tulevaa kannattavuutta selittävä malli, ja sen jälkeen kattavampi malli. Kattavammassa mallissa käytettiin laajempaa joukkoa selittäviä riskimuuttujia kuin yksinkertaisemmassa. Päätestien tilastollista luotettavuutta ja vakautta varmennettiin lukuisilla testeillä.

TULOKSET

Tutkimuksen tulokset osoittavat, että fundamentaalisen riskin ja tulevan kannattavuuden välillä on vahva negatiivinen yhteys high-tech yrityksissä. Tämän mukaan tilinpäätösinformaatiosta lasketut riskimuuttujat ovat hyödyllisiä tulevan kannattavuuden selittämisessä high-tech yrityksillä. Riskisyys näyttää johtavan alempaan tulevan kannattavuuden tasoon. Uusilla listatuilla yrityksillä, joita yleisesti pidetään riskempinä, tämä yhteys on vieläkin vahvempi. Lisäksi havaitaan, että muutama avainmuuttuja riittää selittämään eroja yritysten tulevassa kannattavuudessa, eikä kattavamman mallin käyttäminen lisää selitysastetta kuin marginaalisesti.

Avainsanat Fundamentaalinen riski, kannattavuus, high-tech yritys, regressioanalyysi

Acknowledgements

This thesis has been the biggest project of my life so far. The time between September 2012 and April 2013 has been very challenging and stressful, but also rewarding and enlightening. I have learned a lot about the world of accounting and about doing research. First it was a journey through dozens if not hundreds of research papers, then through hundreds of regression runs.

I could not have completed the study without the help of several people. First I want to thank Assistant Professor Harri Seppänen for providing me the initial data set and guiding me throughout the long research process. The regular meetings were a priceless factor in shaping the paper to what it finally turned out to be. I am also grateful for Professor Juha Kinnunen who gave me valuable feedback in the thesis seminar meetings. Also feedback from other students in the thesis seminar group is greatly appreciated.

I want to thank my friends and family who have supported me during this time and helped me maintain my motivation to complete the study.

Helsinki, 20 April 2013.

Topi Peltonen

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1. Introduction

1.1 Motivation

The aim of this thesis is to study the relationship between fundamental risk and future profitability. Profitability is the most important characteristic in a company. It determines whether a company creates value for its owners (Palepu et al., 2007). Consequently, all the actions a firm undertakes should strive to ensure profitability that meets or preferably exceeds the required rate of return the firm has determined. No matter how well the firm satisfies the needs of other stakeholders, if it does not create sufficient profits for its shareholders, its future survival is endangered. Moreover, the value of a company is based on its future profitability (e.g. Bhattacharya et al., 2010). Thus any new information on the determinants of profitability should be valuable to investors and creditors.

Various arguments about which factors cause the profitability of firms to differ have been made. Cuaresma and Gschwandtner (2008) state that differences in the level and persistence of profitability could exist partly because of differences in risk. They found that risk, defined as the standard deviation of past profitability, is negatively associated with profitability. Qian and Li (2003) report similar results on a small sample study on US biotech SME firms.

The concept of risk is varied in the field of academia. The general definition of risk is the probability of an unwanted event happening. In finance, the main premise is that there is a connection between risk and return. Higher risk is assumed to lead to higher stock returns, and stocks are priced accordingly. French et al. (1987) among others report a positive relationship between stock risk premium and volatility. Fama and French (2005) claim that with rational pricing of stock, highly profitable firms are riskier than average. For credit rating models risk means the probability of default. The probability is expected to rise with the degree of risk in the financial statements.

Nekrasov and Shroff (2009) state that firm value creation of a company ultimately resides from its operating, investing and financing activities, which all combined sum to earnings generation. Keeping this in mind, the authors claim that risk should be measured using these same economic fundamentals as well. In a value investing related study Piotroski (2000) main finding was that financial statement information can be used in distinguishing future strong performers from weak ones. These arguments highlight the importance of using fundamental measures (based on financial statement information) of risk instead of e.g. market based measures. Cuaresma and Gschwandtner (2008) report a negative relationship between profitability and both firm systematic risk (covariance of returns against peers) and volatility of profitability. They reason that this might happen because firms with low profitability are forced to take more risks to try to become profitable. Taken that highly profitable firms are not under such stress, they will thus appear much less risky. The different ways of defining risk make my research setting more vibrant and interesting, as opposing arguments about the relationship between risk and fundamental profitability can be made.

One of the few studies about the profitability of high-tech firms is Qian and Li (2003). They studied which factors influence profitability on a small biotech firm sample. They found that R&D intensity, internationalization and past performance were positively associated with profitability, while risk was negatively. One specific point of interest in the context of profitability is whether a company is profitable in the future (has positive operating profit) or not, and special focus will be devoted to this.

High-tech companies' importance in the modern economy has been increasing continually. Levine (2005) states that small high-techs have a critical role in developing new products and services, hence driving economic growth. Not surprisingly, high-tech firms are a popular sample group for many fields of studies, but issues related to their profitability remain largely uncovered. What a high-tech firm means is not unambiguous. Generally it is defined as a company that designs and produces new products or innovative manufacturing processes by systematically applying scientific and technical knowledge, usually with relatively high Research and Development costs (Hecker, 2005). Barron et al. (2002) found that analysts' consensus is lower and uncertainty is higher on high-tech firms, mainly because of the relatively higher R&D expenditures they have compared to other industries. I argue that this increased uncertainty should show as a stronger association between risk and profitability in high-techs than other industries.

1.2 Research problem

The aim of the study is to find out if risk proxies can be useful in explaining future profitability in high-tech companies. The research problem can be expressed in form of a research question:

Do fundamental risk measures explain differences in future profitability of high-tech companies?

Fundamental risk measures calculated from financial statement information are used in estimating future profitability. I argue that a significant portion of the differences in future profitability can be explained with fundamental risk, i.e. future 'winners' can be separated from 'losers'. I expect that the increased uncertainty of high-techs is associated with future profitability, but due to lack of consensus in former literature I cannot predict in which direction.

There is a countless variety of financial statement figures and ratios, and on the other hand market based figures that have been used in estimating risk. This study does not take a stand on whether it is important to forecast future earnings, share returns, profitability, some other figure or all of these together. The focus is on fundamentals, which means that share returns and other market based figures will not be used.

1.3 Data and research methods

The sample used in the study is a global sample of financial statement figures of 14 749 publicly listed high-tech companies during the period 1990-2010. The data is collected from Thomson One Banker and Datastream databases. The maximum amount of observations available for the most advanced analysis is 32 292, which should be enough to extract significant results. The main empirical tests are done using binary logistic regression and ordinal logistic regression. The analysis is conducted with SPSS and Excel.

I first construct a Parsimonious model that does not use lagged information. Then I build a Comprehensive model that uses also lagged information, but more importantly a wider range of explanatory variables than the simpler Parsimonious model. Each year profitability is explained for the following 1, 3 and 5 years. The dependent variable is primarily a dummy which receives the value 1 when return on assets is larger than 0, and 0 otherwise. The independent risk variables can be divided into three classes: current profitability, general business risk and financial risk. In addition, control variables are used in the models.

As high-tech IPOs are gaining importance in the economy, I also test how fundamental risk explains their future profitability. All models are run first with the whole sample and then with only IPO firms to highlight any differences between the groups.

1.4 Results

The study found that there is a significant association between fundamental risk and future profitability. The association was uniformly negative across one, three and five year periods. When the sample was restricted to IPO firms, the association was found to be even stronger.

I find strong evidence that risk proxies calculated from financial statement information can be used in explaining differences in future profitability of high-tech firms. However, the Comprehensive model has only slightly better explanatory power on future profitability than the Parsimonious one. The difference is so small that the cost of acquiring the additional data and the loss of sample size may not warrant the use of a more complex model. This suggests that a few key explanatory variables, such as in the Parsimonious model, are enough to explain a significant portion of the differences in future profitability. The most consistently influential variables influencing future profitability were found to be current profitability, positive retained earnings and sales.

Evidence suggests that in high-tech firms high fundamental risk leads to lower future profitability, which is contrary to what finance theories suggest. This finding is unique, as similar studies on an international sample of high-tech firms have not been done before. It raises the importance of fundamental risk analysis in high-techs, as it has often been argued that financial statements are not as useful for valuation or estimating future earnings in high-techs as in traditional industries.

1.5 Structure of the paper

The Second Chapter discusses profitability and risk on theoretical level. After that the Third Chapter reviews existing empirical studies firstly on determinants of profitability and secondly on the definition of risk and thirdly on IPO firm unique characteristics. In the Fourth Chapter I go through the research design and form the hypotheses. The Fifth Chapter reports the results of the empirical tests. Lastly, in the Sixth Chapter I conclude the findings of the study.

2. Profitability and risk on theoretical level

2.1 Profitability

Profitability can be determined as a company's ability to make profit, i.e. having revenues larger than costs. It is typically measured either from the point of view of shareholders (return on equity), or both shareholders and creditors (return on assets).

2.1.1 Return on Assets

Return On Assets can be measured in different ways. A key question is whether earnings or operating income should be used as the return figure. Barber and Lyon (1996) argue that operating income (not scaled with number of shares) is a better measure firstly because it is not affected by issues such as tax planning and minority interests and secondly because capital structure changes have no effect on it.

Selling and Stickney (1989) define ROA as net income plus interest expense deflated by the tax rate divided by average total assets. Fama and French (2000) use earnings after taxes plus interest and extraordinary items divided by total book assets at year end. Goddard et al. (2005) use net profit before tax plus interest divided by total assets. Sloan (1996) along with Fairfield et al. (2003) express the formula as operating income after depreciation and amortization divided by average total assets.

As can be seen from the above formula(s), the leverage of the company (debt/equity ratio) should theoretically have no effect on ROA, as the return is calculated on the total assets. It does not matter how this amount of total assets is comprised on the liability side.

As stated in the DuPont model, ROA can also be decomposed into two components; profit margin and asset turnover. Here profit margin means EBIT (Earnings Before Interest and Taxes) divided by revenues and asset turnover is revenues divided by average total assets. *"Asset turnover measures the firm's ability to generate revenues from its assets while profit margin measures the firm's ability to control the costs incurred to generate the revenues."* (Fairfield and Yohn, 2001)

Fairfield and Yohn (2001) argue that the 'mix' of asset turnover and profit margin, of which ROA consists of, only offers information about the company's strategy, but does not help in forecasting future profitability. However, they find that the *changes* in these components can forecast the profitability of one year ahead, i.e. momentum is more important than absolute figures. What is more, all of this correlation comes from the asset turnover component. Piotroski (2000) states that the change in two components of ROA offers additional information compared to only using change in ROA, but he argues that both components are important, and even more so the combined effect of the changes.

To understand which financial statement ratios and figures can have in influence on profitability, we must understand which are the underlying business fundamentals. Selling and Stickney (1989) argue that changes in ROA can occur for three main reasons: change in operating leverage (Fixed assets/Total assets), product life cycle, or differences in the 'ratio' of profit margin and asset turnover.

Sloan (1996) divides ROA into a cash flow component and an accrual component. Further, Fairfield et al. (2003) find that accruals influence not only ROA, but also growth in net operating assets. They continue that both accruals and growth in long-term net operating assets are negatively correlated with the ROA of the following year.

Barber and Lyon (1996) list three main problems emerging from the use of ROA as a measure of profitability: total assets is measured with historical cost instead of their true value, total assets include non-operational (financial) assets and lastly operating income is affected by accruals and thus is potentially 'vulnerable' to earnings manipulation.

An important thing to notice is that ROA should not be compared blindly between different industries, as some industries are more capital intensive than others and as such have different levels of 'acceptable' ROA. In addition, some industries, such as high-techs, have lots of intellectual capital that is not shown in the balance sheet. However, one point worth noting is that when a company has made lots of acquisitions, the goodwill embedded in the balance sheet will arguably show at least a part of the intellectual capital in the firm.

Return on Net Operating Assets (RNOA) means simply operating income divided by operating assets. RNOA is another measure of profitability that can be useful in some analyses.

The formula for Return on Assets used in the study is shown below:

$$ROA_t = \frac{EBIT_t}{Total\ Assets_t} \tag{1}$$

Where EBIT = Earnings before Interest and Taxes at year t.

2.1.2 Return on Equity

The second return figure investors are interested in is Return on Equity. The measure of profitability Pastor and Veronesi (2003) use is earnings divided by the book value of equity.

Unlike ROA, the decomposed formula of ROE includes a component of leverage.

ROE can be expressed as a product of five components:

$$ROE = \frac{Net\ Profit}{Pretax\ Profit} * \frac{Pretax\ Profit}{EBIT} * \frac{EBIT}{Sales} * \frac{Sales}{Assets} * \frac{Assets}{Equity} \tag{2}$$

The different components measure tax burden, interest burden, operating profit margin, asset turnover and leverage, respectively.

Below is a slightly simpler way of decomposing ROE:

$$ROE = ROA + (ROA - i) * \frac{Debt}{Equity} \tag{3}$$

This means that, given that ROA > interest rate (i), ROE is equal to ROA plus the leverage effect of debt.

Another measure of profitability is Return On Common Equity (ROCE). It does not differ a lot from the formula of ROE, but some academics and analysts prefer it. It ignores preferred dividends and preferred equity in the formula. The main components are return from operating activities and return from financing activities. Further, ROCE can be expressed as

RNOA plus financing leverage times the operating spread. Operating spread is the magnitude the company's operations create returns over its net borrowing costs.

Profit margin times asset turnover times financial leverage times spread also returns the same ROCE figure. Here, the main drivers for the components are gross margin and expenses, assets and liabilities and net borrowing cost, respectively.

2.2 Risk

To study the effect of risk on profitability, we need to have clear understanding what risk means in former literature. The conservative definition states that risk is the possibility of a loss or failure. However, in finance literature risk usually also has an upside. Volatility of returns/income is a common measure of this. Malkiel (1982) sums the reasoning behind this measure of risk: for an investor risk is the disappointment of not earning the expected return. The larger the spread around the mean (expected) income, the larger the probability of the figure being negative, i.e. making a loss.

Penman (2010) describes the simplified accounting point of view, residual earnings model, for firm valuation:

$$P_t = B_t + \frac{E_{t+1} - rB_t}{r - g} \tag{4}$$

Where P is theoretical market price of equity, B is book value of equity, E is earnings, g is growth rate of earnings and r is required rate of return or discount rate.

In this approach risk is measured by the discount rate, which can be divided into risk free rate of return (traditionally e.g. government bond) and the company specific risk premium. Penman (2010) states that this premium is usually defined with tools from finance, such as CAPM, no-arbitrage asset pricing model or the Fama-French three-factor model. However, earnings growth is also affected by risk, as growth is never certain to happen. Penman (2010) sums the main idea of his discussion: *"…forecasting is a matter of accounting and accounting has the potential to be revealing about risk. All depends on the accounting principles."* He states that conservative accounting using historical costs smoothes earnings because investments defer earnings to the future and those earnings only really start to show when investments slow down. As earnings are 'moved' into the future, conservative accounting in effect creates earnings growth, which investors assume is risky. There are additional ways of determining the risk premium over the risk-free return. Gode and Monahram (2003) test several of these, and I will discuss them in Chapter 3.2.

Fundamental risk has two main components: ROCE risk and Growth risk. On the other hand it can be divided into two main areas: operating risk and financing risk. ROCE risk is the risk of not earning the expected/required return on common equity. ROCE risk in turn is the product of operating risk and financing risk.

Operating risk has four main components. The first one is *profit margin risk*, which includes expense risk and operating leverage risk. *Expense risk* is the risk of the costs related to the products increasing in comparison to the sales price. *Operating leverage risk* is the risk of the proportion of fixed assets rising in the cost structure. The second component of operating risk is *asset turnover risk*, which means the risk of a decreasing ratio of sales divided by net operating assets. It can happen by declining sales or increasing assets, e.g. because of inventory build-up. The third component of operating risk is *operating liability leverage risk*, the risk of decreasing amount of operating liabilities in comparison to assets. This might be caused by suppliers requiring faster payment, which would in effect decrease ROCE. The fourth part of operating risk is growth risk, which is handled separately in this context, as it has no direct effect on ROCE. *Growth risk* means the risk of adverse business growth.

Financing risk comprises of *financial leverage risk* and *borrowing cost risk*. Financial leverage means the ratio of debt to equity. If this ratio gets too high, the company has no buffer to withstand potential losses and is in effect on the brink of bankruptcy. Financial leverage risk will be discussed in detail in Chapter 3.

The borrowing cost as an absolute figure is not relevant, but the spread between borrowing cost and RNOA. If the company is creating high returns on its operating assets, it can in turn afford to pay high interest rates. However, if the average interest rate surpasses RNOA, every dollar of debt generates losses for the company.

Given that the total risk of a company is a product of operating leverage and financial leverage, Mandelker and Rhee (1984) tested whether companies try to balance these two risks, or whether an increase in the other leads to an increase in the other part as well. The latter could be expected to happen if financial leverage is increased due to the financing of fixed assets (operating leverage). The study found that companies with high operating leverage usually have lower financial leverage, and vice versa. This means that companies indeed balance their total risk level by choosing the amount of financial leverage on the basis of their cost structure.

A central part of a company's riskiness is its *earnings volatility*. The first item in the chain that influences earnings variability is variation in sales. This can be systematic or nonsystematic. Next, operating leverage (as defined earlier) comes into picture. The third item is business risk, which can be either systematic or nonsystematic. Lastly financial leverage determines what is left in the bottom line of earnings variability. As a product of different factors, it has both systematic components that result from market factors, and company-specific factors.

Studies do not usually focus on the risks mentioned above, but more often on either bankruptcy or credit risk, that are more interesting for investors and debtors. The ultimate form of risk realization, bankruptcy, refers to the situation where a company faces such financial distress that it has to discontinue its operations. Credit risk is a similar concept, but it describes the situation from the debtor's point of view; it means the probability of the company not being able to pay its interest and principal payments of its debt.

Scott (1981) argues that theoretically a company goes bankrupt if: 1. Debt payments are larger than EBIT plus present value of future dividends or 2. Payable liabilities are larger than market value of assets. However, both of these clauses are impossible to verify with fundamentals, but the existence of a theoretical basis for bankruptcy is reassuring. Scott (1981) also notes that failing to meet one's financial obligations should not too hastily be used as a synonym with going bankrupt.

In sum, fundamental risk emerges from multiple directions, which means that no single measure of risk can be used in the analysis. Ideally all 'sub-areas' of risk should be addressed with specific risk proxies.

3. Review of empirical studies

With this research setting it is evident that past literature on profitability, risk and high-tech IPOs should be reviewed. Regarding high-tech IPOs, mostly literature relating to profitability or risk is discussed. Literature touching all three aspects of this study is virtually non-existent.

3.1 Determinants of profitability

Goddard et al. (2005) sum the discussion about variation of profitability between companies as follows: strategic management literature explains it with differences in firm resources such as organizational structures and management practices. Industrial economics emphasizes market mechanics of entry and exit. Accounting and finance academics add random walk to the equation to give a better understanding of the variation. Qian and Li (2003) sum that firms can create competitive advantage and thus profits by either exploiting Porter's basic competitive strategies, creating economies of scale or building an attractive brand.

In their empirical study on European manufacturing firms Goddard et al. (2005) found that future profitability is positively affected by past profitability, market share and liquidity, but negatively by size and gearing.

A somewhat separate literature discusses the profitability persistence, or as Fama and French (2000) put it, the mean reversion of profitability. They state that the further away a company is from the industry's average profitability (or an industry is from all industries' average), the higher the probability of moving towards the average. Their empirical results state that the rate of this reversion towards the mean is on average 38% per year. I argue that industry effects of profitability are of special importance especially for high-techs, largely because of the tech bubble that caused virtually all high-tech stocks go down, along with their profits.

An opposing view is stated by e.g. Nunes et al. (2010, 2012), who state that highly (low) profitable firms tend to stay highly (low) profitable also in the next period, similarly to the momentum effect of stock returns. Fairfield et al. (2009) found that growth is industry mean reverting, but profitability is not. They reason that sales growth is driven by general industry level demand patterns, but that costs structures vary a lot inside industries, which leads to varying profitability for the firms. Goddard et al. (2005) also found that in European manufacturing firms profitability is persisting; competitive forces are not strong enough to move profitability towards industry mean in a short one year time span.

McGahan and Porter (2003) make interesting findings relating to industry effects of profitability persistence: industry-wide factors have the largest effect on persistence of high (above median) profitability. Naturally for low performance, business-specific factors and, in case of conglomerates, the effect of corporate parents are more important. Also interestingly, the study found that high performance is preceded by a period of high performance. McGahan and Porter (2003) claim that this contradicts with the basic statement that companies need to 'suffer' investment periods of low profitability to reach high profitability. Also, low performance tends to continue for long periods. The authors reason that once a firm 'ends up' in the low profitability group, it is hard to return to above average profitability e.g. due to a 'lock down' of an unprofitable strategy. In conclusion, McGahan and Porter (2003) present strong arguments against the mean reversion theory of profitability.

Be the prevalent theory either mean reversion or persistence of profitability, past profitability seems to be an important factor in forecasting future profitability. As the focus point of this study is whether a company has a positive profitability in the future, obviously the main point of interest should be whether the firm is currently above or below this line. However, most of the findings of studies measuring absolute profitability are relevant to this research setting as well. Common sense dictates that firms with currently low (negative) profitability are risky, i.e. they are likely to have low profitability also in the future. However, Barron et al. (2002) found that the effect of past earnings on future earnings is lower for companies with relatively high R&D expenses, like many of the firms in the high-tech sector.

3.2 Risk

Risk is one of the most studied concepts in finance and accounting. In this chapter I go through two important issues: what kind of 'warning signals' former studies have found about future insolvency and what kind of effect does risk have on firms.

3.2.1 Credit risk indicators

Bankruptcy and credit rating models describe and measure risk in their own ways. It is important for my study to determine what are good measures of risk.

Standard & Poor's (one of the two major rating agencies) published the medians of key financial ratios of industrial US companies belonging to specific rating classes in 1998-2000 (though the agency states that the values are merely medians, not any sort of requirements for achieving a specific rating). From the table it can be seen that the ratios improve exponentially when moving from CCC-class to AAA-class. This means that even if a company has ratios twice as good as a CCC-rated company, it is still considered very risky by the rating agency. As the credit ratings of the two major rating agencies seem to be quite widely trusted (at least they were before the financial crisis, where unique market conditions showed major flaws in the ratings), I argue that the variables shown above can be considered as good, general measures of (credit) risk.

S&P also published the guidelines of the funds from operations (EBITDA) divided by total debt figures for specific credit ratings in 2002:

Table 1: S&P Funds from Operations to Total Debt Guidelines

Source: Standard & Poor's 2003

U.S. INDUSTRIALS

Manufacturing, Service and Transportation Companies

Funds from Operations/Total Debt Guidelines (%)

	—Rating category—				
Company business risk profile	**AAA**	**AA**	**A**	**BBB**	**BB**
Well above average business position	80	60	40	25	10
Above average	150	80	50	30	15
Average	—	105	60	35	20
Below average	—	—	85	40	25
Well below average	—	—	—	65	45

In addition, the company published the guidelines for total debt divided by capitalization in 2002:

Table 2: S&P Total Debt to Capitalization Guidelines

Source: Standard & Poor's 2003

Total Debt/Capitalization Guidelines (%)

	—Rating category—				
Company business risk profile	**AAA**	**AA**	**A**	**BBB**	**BB**
Well above average business position	30	40	50	60	70
Above average	20	25	40	50	60
Average	—	15	30	40	55
Below average	—	—	25	35	45
Well below average	—	—	—	25	35

These tables clearly show that business risk and financial risk are directly connected in the mindset of credit rating agencies. Companies with above average risk are required to have much healthier financial statement figures to show they can handle the extra business risk financially. The highest AAA-rating is even unreachable for even companies of only average business risk level, notwithstanding their financial health. Blume et al. (1998) tested different credit rating models and found that credit rating agencies are actually prone to giving worse ratings with a given mix of financial ratios than they used to be.

3.2.2 Effects of risk

The realization of a risk is usually considered a serious matter for firms. What consequences a firm has to face in case of a delisting (both voluntary and involuntary)? Macey et al. (2005) studied 2002 US delists and found that a stock loses as much as half of its value on average, doubles its spread and doubles its volatility when moving from the public stock exchange to a private over-the-counter market. Unlike one might expect, they found that during 1999-2002 only ~30 percent of delistings in NYSE and ~14 percent in Nasdaq stock exchanges listed bankruptcy as a reason for delisting.

Beaver et al. (2005) studied the financial ratios of US firms that have gone bankrupt (about 0.7% of the population of over 70 000 firm years) during 1962-2002. They found that while the median ROA of the population is 6%, for the companies that go bankrupt the ROA starts deteriorating early. Four years before bankruptcy date it is 1%, two years before -4% and a year before as low as -12%. Similar development can be seen with debt/asset ratio: population has a median of 0.51, four, two and one year before bankruptcy the ratio is 0.67, 0.76 and 0.85, respectively. The means in both cases are even lower, suggesting that the distribution is highly skewed towards the worse values. An overly simplified conclusion would be that it is easy to see the signs of a coming bankruptcy already years before. Naturally more research is needed than just a quick glance at some statistics, especially with a sample such as mine that consists of high-tech firms only and uses newer data.

A potential risk for all investors, especially in the IPO group, is information risk. It means the problem of the financial statements not containing enough information or information of adequate quality about the risks associated to the company.

Li et al. (2012) found an interesting factor that influences corporate risk taking; national culture. They show that managers from individualistic countries are more prone to risk taking. What makes managers take less risk is a culture with high uncertainty avoidance and a quest for harmony (values peace, environmental issues and beauty). It could thus be generalized that firms operating in individualistic countries are riskier, and those in harmonic and uncertainty avoiding countries are less risky. Country dummies should nullify this effect, as it is impossible to reliably model this in the tests.

One way of estimating the risk of a company is by calculating the risk premium for its stock. Gode and Mohanram (2003) define it as follows: *"The risk premium is a summary measure of risk as perceived by equity investors and is the critical link between stock prices and earnings forecasts."* They tested three ways of estimating the risk premium: the Ohlson-Juettner model and the more traditional Residual Income Valuation –model (RIV) both by excluding (RIV1) and including (RIV2) negative ROE companies. The study found that the RIV1 model is most fitted for predicting future stock returns. This implies that in risk estimation some industry measure should be used, but firms with negative profitability should be excluded. The RIV1 model also outperformed in estimating the actual risk premium that can be calculated from the current share price on the stock market.

In general, credit risk models rely more on financial statement figures, while bankruptcy models focus on other factors, e.g. market based variables. Nekrasov and Shroff (2009) state a common challenge with measures of risk: *"…if risk originates from fundamentals, a 'good' measure of risk ought to be estimated from more primitive variables than returns. Yet, returns-based measures of risk are the practical norm, and their observed correlation with accounting risk measures is generally offered as evidence that the source of risk captured by these measures can be traced to economic fundamentals."* They continue that fundamental based measures of risk are especially useful for valuation of companies with no previous return data available, such as IPOs.

Francis and Schipper (1999) likewise argue that the value relevance of returns figures is decreasing, while the relevance of financial statement figures is increasing. In line with what is expected is their finding that financial statement figures are slightly less relevant for high-tech firms than for other companies. I believe this also gives support to basing the analysis mainly on financial statement figures, instead of market-based measures of risk. Stock analysts have also recognized this.

Campbell et al. (2008) go along the lines of Nekrasov and Shroff (2009) when they state that based on their model, *"variations in leverage, volatility, price per share, and profitability are more important for failure risk than movements in market capitalization, cash, or the market-to-book ratio"*. They found that if firms are arranged in portfolios based on their level of failure risk (measured by their own model), the least risky portfolio clearly exceeds the average market stock return, while riskier portfolios linearly show decreased returns. The riskiest portfolio show sizeable negative excess returns. Given that there are no unique market events during the sample period, the authors give two possible reasons for these results: investors systematically undermine failure risk in their valuations or because they have motives unexplained by financial theories to hold the underperforming stock, e.g. to extract private benefits from the company as a majority owner.

Some studies have claimed that the extreme performers (both winners and losers) come from the same group of firms. Beneish et al. (2001) argue that a two-stage model should be used for evaluating firms. On the first stage their model uses mainly stock market data to determine which companies are expected to have 'extreme' returns. Extreme performers are more likely to be newly founded and small firms with high sales growth, return volatility, R&D intensity and recent trading volume with a lower sales-to-price multiple than average. The second stage of the analysis, mostly founded on financial statement figures, aims to find out which of these extreme performers are going to be 'winners' and which of them will in turn be 'losers'. In the extreme performer group the following signals predict weak performance instead of strong: low sales growth, operating margin, R&D spending along with negative earnings surprises, bad recent price performance, high proportion of accruals and CAPEX. The variables the study uses on both stages of the model can be useful also for explaining profitability in my study.

Mohanram (2005) shows that fundamental analysis aimed at predicting future stock returns should be used differently for low B/M (Book-to-market) stocks and high B/M stocks. Low B/M firms ("growth companies") that are generally considered riskier should be evaluated with Mohanram's GSCORE-method, which uses the following 'fundamental signals' that are compared to industry median: ROA, Cash Flow ROA, Variance of ROA, VARΔS, R&D, Capital intensity, advertising expense intensity and lastly a variable of CFROA divided by ROA. High B/M firms ("value companies") should on the other hand be analyzed by using Piotroski's (2000) FSCORE (current profitability, ΔROA, cash flow sign, Cash flow to Net income, ΔOperating margin, ΔAsset turnover, ΔLeverage, ΔCurrent ratio, Equity issue (Y/N)).

These ‘scores’ are simple to calculate and interpret, but they potentially lose some information when a factor only gets a binary value and the strength of the signal is not taken into account. In addition, they assume that all factors are equally valuable for the future performance of the company. However, both of these scores contain variables that could be used in forecasting future fundamental profitability as well as stock returns. As high-techs are usually positioned in the growth company section, GSCORE seems more viable for my study. Mohanram (2005) however points out that the large excess returns a GSCORE-based investment strategy yields are very dependent on short-selling the ‘loser’ stocks, i.e. GSCORE is much better at identifying weak companies than strong ones. Finally he states that low GSCORE firms have much lower returns, even though their systematic, unsystematic and ex-ante risk is higher. This finding supports a negative association between risk and return in this subgroup.

Fama and French (2005) make a bold claim about stock values and risk: *“With rational pricing, the book-to-market, profitability, and investment effects in expected returns implied by the valuation equations are due to differences in risk: controlling for other variables, more profitable firms and firms with higher book-to-market ratios are more risky, and faster-growing firms are less risky.”* The argument about growth is quite unorthodox, as growth is traditionally thought to be risky. What is more, in effect Fama and French (2005) state that unless markets price assets irrationally, profitable companies are riskier than unprofitable ones. However, like mentioned earlier, Cuaresma and Gschwandtner (2008) make an opposing argument; less risky firms tend to have more persistent profitability both in the short and in the long run. This is of course contrary to the finance theories, where higher profits are expected to be the result of higher risk taking. The same study also found that both sales growth and firm size are negatively associated with profitability.

Weyns et al. (2011) describe the traditional way of equity analysts’ risk estimation as first converting their price target into a return figure, then subtracting from this some market-based required return, such as market beta or volatility of returns. However, they state that nowadays stock analysts use much more sophisticated methods in estimating risk: *“Modern-day research in financial economics—much of which has proven to be useful in investment* *practice—comes to grips with uncertainty by considering any value driver (e.g., revenue, cash flow or earnings growth) to have a set of probabilities for the range of possible future outcomes. Such an approach begins with the premise that any risk factor, including fundamental value drivers, can be summarized by the probability distribution of its possible future values—and that the risk itself can be quantified by the standard deviation of that distribution"* This seems to be the way analysts work, but this kind of method can only be used when detailed information about the firm is available.

Shumway (2001) developed a hazard model for predicting bankruptcy. The difference between a static model and a hazard model is that a hazard model accounts for time. A company's bankruptcy probability is a function of the time it has spent in the 'risky group'. *"The hazard model classifies almost 70% of all bankruptcies in the highest bankruptcy probability decile. It classifies 96.6% of bankrupt firms above the median probability."* (Shumway, 2001) It would seem that not only fundamentals are important in predicting bankruptcies, but timing as well. A company may be able to 'handle' short timeframes of 'bad' fundamentals, but as time passes with no change in the situation, the probability of bankruptcy increases.

In their study about analysts' earnings forecasts, Joos et al. (2012) found that the spread between the optimistic and pessimistic scenario in the forecast is widened with risk. Thus, when even the highly informed analysts (I do not take a stance on whether analysts' forecasts can or should be trusted, despite the recent criticism) do not find common ground in determining the risks and value of certain companies, it can be argued that the uncertainty in these companies is very high. The most relevant measures of risk the researchers found were systematic and idiosyncratic risk, market beta, B/M ratio, small size, leverage and operating loss. These variables are used in many of the studies mentioned earlier and this provides additional support for the notion that risk and profitability are connected. Lui et al. (2007) report similar results with risk proxies, with the addition of earnings quality to the mix.

A big element in risk is uncertainty. It could even be said that risk is just uncertainty about the future (cash flows). Pastor and Veronesi (2003) found that uncertainty about future profitability actually increases stock valuations. They also found that this uncertainty decreases over time, thus making newly listed companies the most overvalued, with the effect decreasing over the firm life-cycle. Additionally, the authors point out that the volatility of profitability (ROE) has risen from 10 percent in 1963 to over 40 percent in 2000, caused e.g. by the relaxing of the barriers for new companies to the market. I argue this makes forecasting profitability even more important.

When talking about fundamental risk, some of the total risk is visible in the income statement, while some can be seen in the balance sheet. Both static figures from balance sheet at year end (or year averages) and dynamic volatility figures should be used in getting a full picture of a company's risk.

3.3 Profitability and leverage

The relationship between profitability and leverage has been studied from different angles in accounting, finance, strategic management and industrial economics literature. If we reflect back to the theoretical formula of ROA, the amount of leverage a company has in its balance sheet should not have a direct effect on ROA. However, it can potentially have an indirect effect on ROA through increased probability of financial distress that is associated with leverage. Empirical studies touching this aspect will be reviewed below.

Titman and Wessels (1988) found a negative correlation between leverage and profitability. However, at the same time Bhandari (1988) found that leverage and future stock returns are positively correlated. Nunes et al. (2012) found a positive relationship between liquidity and profitability. They also found a negative relationship between long term debt and profitability. Goddard et al. (2005) report a negative relationship between a firm's gearing ratio and profitability, and likewise a positive correlation between liquidity and profitability.

One of the few empirical studies that found positive correlations between risk and profitability is Adams and Buckle (2003). They studied Bermuda insurance companies' financial performance while considering multiple risk measures. They found that the most profitable companies had higher leverage, lower liquidity and engaged in the riskiest underwriting business. This context is obviously quite unique, but it is worth studying if something similar could be happening with high-tech (IPO) companies, since they are also quite different from traditional manufacturing companies, on which most of the existing research on profitability has focused on.

Goddard et al. (2005) regressed ROA with ROA of one and two years before the period, total assets, market share in product market, gearing ratio and liquidity ratio. They state that high gearing ratio on the other hand places the firm at greater risk of not meeting interest and debt payments, but on the other hand benefits shareholders if the profit exceeds the costs of borrowing. Their analysis found a negative relationship between gearing ratio and profitability and a positive relationship between liquidity and profitability.

Bevan and Danbolt (2002) explain the negative relationship between profitability and leverage by stating that the more profitable a company is, the better its access to debt is, but conversely the less it needs additional debt financing. In this case, when forecasting profitability, all the information about low leverage would already be included in the measure of current profitability. Modigliani and Miller's (1963) classic theorem however might turn the scale towards issuing more debt because of tax shields offered by it. The opposing argument by Bevan and Danbolt (2002) is the pecking order theory by Myers and Majluf (1984), where internal (equity) financing is always prioritized. With single year (1991) UK data Bevan and Danbolt (2002) regress gearing with profitability among other variables. They find that the correlation is highly and significantly negative, but it is stronger when using book values and also when simple debt-to-capital measures of gearing are used. What is interesting is that the correlation between profitability and short-term debt is much stronger than with long-term debt. Chen (2004) reports a negative relationship between gearing and profitability in Chinese companies. Again, the correlation is much higher with total debt than long-term debt. In accordance with this many of the bankruptcy or credit risk models also make distinctions between short-term and long-term debt. Sogorb-Mira (2005) had similar results with Spanish SMEs; short-term debt had a strong negative correlation with profitability, while long-term debt's correlation was barely below zero, though still statistically significant.

Chittenden et al. (1996) used UK small firm data and found no statistically significant connection between long-term debt and profitability, but like many others found significant negative correlation between short-term debt and profitability. They, too, rationalize this phenomenon by profitable companies not having to resort to short-term debt, but rather retained earnings in financing their investments. Additionally, they make an argument relevant to IPOs: unlisted firms need to rely on collateral to acquire funding, while after listing profitability is the requirement. This would imply that after the point of listing, only (highly) profitable companies would issue debt, thus giving a positive correlation between the two variables. Piotroski's (2000) study with high B/M firms in the US gives support to this claim. Variables he used include the changes in liquidity (current ratio) and in leverage (long-term debt). Both change in liquidity and change in leverage were positively correlated with change in profitability (ROA), with the latter result being quite surprising.

Nunes et al. (2010) sum the findings of Lensink et al. (2005*): "SMEs reduce presumably less efficient investment in high-risk situations, and so greater level of risk does not necessarily mean diminished profitability."* Nunes et al. (2010) however found some evidence for the negative relationship between risk and profitability in Portuguese SMEs. In their later study Nunes et al. (2012) also found evidence of a positive relationship between liquidity and profitability in young SMEs, which in their opinion contradicts with former studies which state that (excessive) liquidity can lead managers in investing the "slack" funds into unprofitable projects. Nunes et al. (2012) also make an interesting finding that contradicts with their former study; long-term debt and profitability in young SMEs are positively correlated. They reason that this is due to these firms having better opportunities for taking on new investment projects that are available especially in the start of their life-cycle.

As stated earlier, ROA is the most common measure of profitability used in research of this area. However, Nissim and Penman (2003) separate both the income statement and the balance sheet into two: operations and financing. They then calculate Return on Operating Assets (ROOA) instead of ROA. This approach, in my opinion, has its problems, as the company would not be able to operate without its financial assets, and thus calculating this separate return on operating assets seems perhaps arbitrary. Yet, the study offers some insights on profitability:

"One might well conjecture a positive correlation [between leverage and profitability]. Firms with high profitability might be willing to take on more leverage because the risk of the spread [between ROOA and borrowing rate] turning unfavorable is lower, with correspondingly lower expected bankruptcy costs. We suggest that leverage is partly an ex post phenomenon. Firms that are very profitable generate positive free cash flow, and use it to pay back debt or acquire financial assets"

So in fact Nissim and Penman (2003) found that not only the duration of leverage (short-term or long-term) matters, but more appropriately whether the debt is used as financial or operating liability leverage. They report that this contrast is clear; while financial leverage is negatively correlated with ROCE (Return on Capital Employed), operating liability leverage is positively correlated with both RNOA (Return on Net Operating Assets) and ROOA. This raises the importance of selecting the variables used for my regression model carefully, as otherwise the results might be inconclusive or faulty.

Panno (2003) looks at leverage from a different perspective: not only the current leverage, but the propensity of issuing either new equity or debt. He argues that "*leverage ratio should be negatively related to the risks faced by the firm, as primarily determined by the variability and uncertainty of its sales and costs.*" He continues that risky companies (as determined by their market beta) should have lower leverage ratios. Panno's (2003) findings are interesting: profitability is positively correlated with new debt issues. He argues that this happens because of the tax shields profitable companies can take advantage of, or because lenders give out debt to profitable companies either more easily or simultaneously with lower interest rates, thus making it more attractive.

However, when it comes to studying the effect of leverage on profitability in high-techs, and especially IPOs that initially have abundant cash from the offering, it is worth noting the possible lack of debt and thus inexistent association between leverage and profitability:

"The role of leverage may be different for non-tech versus high-tech firms, however, since firms with more tangible assets in place are more likely to have significant debt as a natural part of their financial structure whereas the long-term financing of high-tech firms is predominantly in the form of equity." (Demers and Joos, 2007)

Carpenter and Petersen (2002) concur with this, as they describe how attaining debt is difficult for high-techs because most of their investments are related to R&D, which have little collateral value, because most of it is in fact salaries, and the remaining part of physical assets is often very company-specific with little external value. Carpenter and Petersen (2002) continue that because of this, the primary source of funding new investment projects for high-tech IPO firms is the issued equity and after that retained earnings from operations. The authors note that seasoned public offerings are usually avoided. As these companies often require a long time to achieve (high) profitability, their ability to undertake new (profit bearing) investment projects is restricted, unless the initial offering is large enough to provide funds for investments and operations for a longer time period. Emerging from this is a potential factor explaining future profitability for high-tech IPOs: the relative size of the equity offering (e.g. Issued equity/TA).

It should be noted that if the sample used in this study includes mostly companies with little debt and thus little interest expenses, ROA and ROE will be quite identical figures, which reduces the importance of selecting either of these ratios as the dependent variable.

3.4 IPO characteristics

A company can be determined to be in its 'IPO-stage' of life for the first few years after its stock listing. It is commonly believed that during this time the firm behaves differently in the market. In my study, however, IPOs are analyzed separately only in terms of their listing year.

An increasing amount of all IPOs nowadays are high-tech companies (Demers and Joos, 2007), which raises their importance in the stock market. Since high-tech company is a relatively new concept, there is not as much research about them as e.g. traditional manufacturing companies. Additional motivation for selecting high-techs is that e.g. Beneish et al. (2001) stress the importance of basing fundamental analysis on a specific subset of firms such as a single industry for better comparability of financials.

Jain et al. (2008) state that the birth of internet companies especially in the tide of the millennia changed the IPO market in a way that listing companies don't have to be profitable anymore. Instead they have to have a good promise of future profitability. It could thus be hypothesized that risk factors provide hints for finding the companies that will achieve future profitability. I argue that firms with negative profitability and no established customer base or even a market-ready product should always be considered as risky.

Many studies have found that riskier IPO firms are more likely to fail and thus the relationship between e.g. leverage and profitability has mainly been negative in past studies. Few studies have tried to uncover if some of the riskiest firms are actually in the future among the most profitable. For example Lowry et al. (2010) have reported that the both the initial returns (first 21 trading days) and the volatility of returns are exceptionally high for IPO firms. This can be interpreted to mean that the uncertainty about the future profitability of the firms is on a very high level. Consequently, this should lead to the relationship between risk and future profitability being higher. Additionally, Demers and Joos (2007) claim that even though IPO valuation is more about stock market data, IPO failure risk is better predicted by financial statement information, i.e. risk can be estimated better from financial statements than market sentiment.

It has been reported by e.g. Clementi (2002) that IPO profitability decreases after listing. Related to this, an issue about measuring the profitability of IPO companies is presented by Barber and Lyon (1996). The listing company often overstates its earnings to increase the demand on its offering, leading to a situation where the company has a very hard time to even reach the same level of profitability as before listing. Barber and Lyon (1996) offer a solution: using cash flow ROA as the profitability measure. This ignores the effect of accruals and gives a better picture how the profitability has changed during the IPO year. However, the authors note that generally accrual returns are more informative, and that cash flow returns should only be used in specific situations to ascertain that a drop in profitability is not only due to earnings management.

Clementi (2002) offers another explanation for the decreasing ROA: the mathematics underlying both in the ROA formula and the balance sheet changes happening in the IPO. As the denominator in the ROA formula naturally increases with an IPO, to stay on the pre-IPO level of profitability also the numerator, earnings, should increase in proportion. However, this is generally not the case, as the new investments made with the funds gained from the equity issue take a longer time to start producing cash flows. Clementi (2002) further strengthens his argument by dismissing the pre-IPO earnings management explanation offered by many by showing Jain and Kini (1994) test results that exhibit ROA declining even more after the IPO year. In sum, arguments can be made for both increased or decreased importance of current profitability for future profitability in IPO firms.

The amount of profitable IPO companies has been decreasing at the same time as the number of IPOs has been increasing. Ritter and Welch (2002) report nearly two thousand IPOs in the 1980’s, of which 81% had earnings per share larger than 0. During the internet bubble the amount of IPOs per year doubled, but only 21% of the firms were profitable. This massive change is in part due to the amount of technology companies in the IPO population rising from 26% to 72%. Jain et al. (2008) state that since the burst of the internet bubble listing companies are not expected to be profitable at the time of listing, but instead they should have a credible "path-to-profitability", a specific timeframe when profitability is expected to be achieved. Perhaps risk proxies can help in identifying the companies with likely success in reaching profitability.

Lui et al. (2007) report, in line with other studies, that IPO firms are more likely to be rated risky by analysts, though this effect is not statistically significant in all cases. Even though IPO firms are usually considered riskier than more seasoned firms, Eckbo and Norli (2001) state that when IPOs are matched with seasoned companies on the basis of size and B/M, listing companies actually have lower leverage and higher liquidity. It appears that risk is perhaps not visible in the fundamentals of IPOs, but in the market sentiment, where IPOs are automatically expected to be more likely to fail.

In addition to the aforementioned variables of leverage and liquidity, Bhattacharya et al. (2010) mention another possible risk proxy for IPOs; accumulated deficits (this does not necessarily mean high leverage). They argue that high accumulated losses can be a sign of higher failure risk. However, Demers and Joos (2007) argue that in the high-tech sector they can indicate high past spending on intangible assets, namely research and development expenses. This in turn would not tell of higher risk, but on the contrary higher future potential for success. This will be an interesting variable to study in relation to profitability.

One thing worth noting about high-tech IPOs is the reason why they issue the IPO. Do high-tech companies go public to gain access to more equity capital for making investments or stabilizing the balance sheet, or to cash in their founders' or venture capitalists' holdings when the company has become valuable enough? (Jain and Kini, 1999) The adverse selection theory states that the owners issue the IPO when the profitability of the firm is at its peak, and the only way to determine whether this is really the case is to look at the amount of shares the founders retain. The larger the founders' share after the IPO, the less the profitability should decline, and as the market 'knows' this, they are willing to pay a higher price for the shares. Additionally, high ownership retention by the founders reduces the moral hazard problem in the company, which should also show as higher profitability (Clementi, 2002).

Pastor et al. (2007) argue that firms issue IPOs because the owners want to diversify their holdings. They reason that the best moment for the offering is when the expected future profitability is highest and when the (anticipated) market value exceeds the private value for the owners. Like others before, the study found that profitability generally drops after the IPO. This effect is strengthened with the volatility of profitability and with uncertainty. When building their model Pastor et al. (2007) faced a dilemma, as uncertainty is often measured with volatility. However, they came up with a rather unusual measure for uncertainty to separate it from volatility: earnings response coefficients. The results of the study show that profitability after IPO drops more if volatility of ROE (or ROA) is high, but quite surprisingly also when uncertainty is low, not high.

Piotroski (2000) takes equity issues (not exclusively IPOs) as negative signals for firms' future performance. He argues that equity offerings show that the company is not able to generate funds internally. In my opinion this is hardly the case, as companies need funds to undertake large investment projects and to promote growth at the proper moment, not only after their business has created enough funds.

Jain et al. (2008) present a way unique to IPOs for estimating risk; the number of risk factors listed in the IPO prospectus. Their study found that the listing companies that eventually achieved profitability had a median of 28 risk factors listed in the IPO prospectus, while the to-be unprofitable ones had 33. Naturally the estimate of the management at the time of listing is somewhat biased, but it provides information about a potential link between risk and profitability in high-tech IPOs.

In Chen's (2004, p. 1342) capital structure theory summary, he states that on one hand gearing should be negatively correlated with profitability as stated by the pecking order theory, but on the other hand positively correlated as suggested by trade-off and signaling theories (Similarly in Panno, 2003). Reflecting on this, it seems that pecking order theory is more prevalent in almost all markets and studies, as the correlation is found to be negative. This leads to the conclusion that if either trade-off theory or signaling theory were to be stronger, or pecking order weaker, in some case (e.g. listing high-techs), that would theoretically lead into a positive correlation between leverage and profitability. However, Sogorb-Mira (2005) further weakens trade-off theory in this context when he states that SMEs (arguably also applicable to IPOs) are less likely to be profitable and thus less likely to get any benefit from tax shields, leading to them not preferring to issue debt like the trade-off theory would suggest.

4. Research design

4.1 Hypotheses

As stated before, high-tech companies have very uncertain expectations for future, especially at the point of stock market listing. Probably many of them will go bankrupt relatively soon after their listing, but some of them will also become very successful companies earning their founders fortunes.

Beneish et al. (2001) sum their findings from US stocks during 20 years: *"We show that extreme losers and extreme winners share many common traits. These common traits make it difficult to isolate 'torpedo' stocks (extreme losers) from 'rocket' stocks (extreme winners) using standard techniques."* On this basis, it is hard to say whether certain risk characteristics on average predict a profitable or unprofitable future for the company.

H1: Fundamental risk is associated with profitability at t+n (n=1, 3, 5) years in high-tech firms

Hypothesis 1 states that fundamental risk measures can explain differences in the future profitability of high-tech firms. Finance theories state that in investments there is a positive relationship between risk and expected return. Investors of a risky company expect higher future stock returns than market average. Since stock returns ultimately depend on the underlying cash flows, i.e. profitability, I argue that risk should be able to explain a part of why some companies become more/less profitable than others.

The expected direction of the association cannot be reliably stated. Especially among high-techs the effect of fundamental risk on profitability is largely unknown. Finance literature talks about the relationship between risk and *expected* returns, which should be positive. However, a large portion of those firms fail to meet the expectations, which should lead to the average profitability dropping. Qian and Li (2003) found risk to be negatively associated with profitability in biotech SMEs, but the effect was quite weak and only statistically significant on the 10 percent level.

The timeframe I expect the relationship to exist is short to medium, as for long timeframes such as 10 years it would be very hard to even find companies in this industry that have been listed for such a long time. Additionally, random effects would be likely to have too much influence and so would diminish the explanatory power of the regressions.

H2: High-tech IPOs have stronger association between risk and profitability than seasoned companies

Pastor and Veronesi (2003) state that there is high uncertainty about the future profitability of IPO firms, which leads to high initial volatility of returns for those firms. Given that high-tech IPOs are both more likely to fail and on the other hand to become very profitable, it seems logical that there was a link between risk and profitability that is stronger than in the less risky seasoned firms. In this case models should have higher R-Squares and overall classification power when the sample is restricted to IPOs. There is less financial statement information available for IPOs, which means that the analysis has to be based on basic figures only.

H3: Using more a more comprehensive set of historical fundamental risk figures increases the explanatory power of the model

As explained in Chapter 3, it has been argued that a more complex analysis involving specifically the use of historical financial statement figures i.e. growth and volatility variables and possibly dividing variables into more specific components gives a more complete picture of a company and should thus also give more accurate predictions about future profitability. However, financial statements of year t should by definition give as true as possible a picture about the financial situation of a firm, so it can be argued that using former published figures should not bring any additional prediction power about the company's future. Also, a few key figures can already contain enough information, thus rendering the use of a complex set of figures useless.

4.2 Data

The main empirical research method is statistical analysis using SPSS and Excel. Data is gathered from Thomson One database and Worldscope database. The report includes descriptive statistics of the sample, correlations between variables and the regression output of different models.

The sample consists of 14 749 companies around the world defined as high-techs by their NAICS 2002 code. Firms from the following sub-industries are included in the data: 3254 Pharmaceutical and medicine manufacturing, 3341 Computer and peripheral equipment manufacturing, 3342 Communications equipment manufacturing, 3344 Semiconductor and other electronic component manufacturing, 3345 Navigational, measuring, electromedical and control instruments manufacturing, 3364 Aerospace product and parts manufacturing, 5112 Software publishers, 5161 Internet publishing and broadcasting, 5179 Other telecommunications, 5181 Internet service providers and web search portals, 5182 Data processing, hosting and related services, 5413 Architectural, engineering and related services, 5415 Computer systems design and related services and 5417 Scientific research and development services. As mentioned in the Introduction, the reliability of fundamental analysis increases when it is based on a subset of companies that have similar characteristics, such as a single industry. The industries listed above of course differ significantly and companies inside the sub-industries are not identical either. Yet, some kind of narrowing down of firms into a more homogenous group is achieved with this industry focus.

The research period is 1990-2010 due to data availability issues. This is the longest timeframe reliable data on high-techs can be gathered. The analysis is based on years 1991-2009 so that enough lagging data and forward data can be acquired for each respective year. When we calculate 14 749 times 21 years, we get a theoretical maximum number of observations for analysis of 309 729. However, in practice the maximum amount of cases for the most simple analysis is the total amount of ROA figures: 99 146, 32 percent of the cases. This seems like a relatively low number of total cases, but if we select only e.g. year 2006 (the year with the largest amount of cases), we see an increase in the percentage of cases available to 61%, which is a substantial increase. Of the 99 146 valid cases 6 265 are IPOs. 1 834 sample companies delisted from the stock exchange. The companies in the data were identified as new lists the year they appeared in the closing price data.

An important issue concerning the data is delisting. A portion of the companies that appear in the sample eventually delist and thus disappear from the remaining sample years. The delisting can be because of bankruptcy, acquisition or some other reason, e.g. voluntary delisting to ease reporting burden or simply no longer fulfilling the stock exchange's requirements for listed companies. The question is how delisting should be taken into account in the model to avoid delisting bias, and whether different delisting reasons should be handled differently.

Table 3: Basic descriptive statistics of whole sample

		Sales	EBIT	Tassets	Mcap	Tdebt	ROA
N	Valid	106985	101493	100101	116739	99816	99146
	Missing	202408	207900	209292	192654	209577	210247
Mean		778.97	66.65	1019.27	1166.31	243.34	-11.26
Median		47.50	0.86	50.39	49.50	3.57	0.03
Std. Deviation		4535.88	2427.91	7363.29	8828.40	2106.67	2230.39
Skewness		13.34	-38.00	18.46	19.64	21.19	-294.23
Kurtosis		233.13	41667.40	467.19	557.94	573.42	89736.61
Minimum		-680.79	-552000.00	0.00	0.00	0.00	-684768.00
Maximum		136250.18	482000.00	275644.00	460304.06	81968.70	5474.33
Percentiles	0.1	0.00	-1698.14	0.00	0.00	0.00	-259.46
	1	0.00	-148.25	0.02	0.00	0.00	-11.89
	10	0.64	-12.09	2.67	1.63	0.00	-0.72
	25	9.31	-2.40	12.72	10.37	0.11	-0.16
	50	47.50	0.86	50.39	49.50	3.57	0.03
	75	202.22	9.74	201.75	228.59	27.83	0.10
	90	877.55	54.68	908.90	1027.47	174.89	0.17
	99	16692.43	1691.30	21451.57	21674.83	4967.71	0.41
	99,9	69018.90	10288.00	113096.02	137674.76	28998.05	2.05

Sales = Annual gross sales, EBIT = Earnings before interest and taxes, Tassets = Total Assets, Mcap = Market capitalization, Tdebt = Total debt, ROA = Return on assets (EBIT/Tassets)

In Table 3 are presented some basic fundamental figures for the whole sample. All numerical values are in millions of US dollars. It can instantly be seen that all of these variables are very skewed and leptokurtic. If the skewness value is more than 3 and kurtosis value more than 4-8 (as absolute figures) as is the situation here, it can be said that the data has several violations of normality. The sample also contains a large amount of outliers, and the medians and means are very far apart from each other. This means that some transformations of the variables used in the models will be necessary to make the results statistically reliable. It can be seen that the companies in the sample are mostly small, with the exception of a few large multinational companies. For example, 10% of the sample companies have Sales larger than $877.55M.

ROA

Since the early 1990's the average ROAs of high-tech companies have gone through a significant change. The average ROA of the best 5 percent of companies has remained quite stable; decreasing from 26.18% in 1990-1994 to 21.99% in 2006-2010. However, there has been a dramatic change in the performance of the bottom 5% of companies: in 1990-1994 the average ROA was -103.57%, while in 2006-2010 it had sunk to -202.11%.

This might partly be due to the fact that data is available for only a very small proportion of all companies in the earliest years of my data, and the companies included are likely to be among the most successful ones, which would lead to a positive bias in the profitability of these companies. However, as was explained before, the relaxation of stock listing criteria and the increase of competition has lead to a steep increase in the amount of very unprofitable listed firms.

When it comes to Jain et al. (2008) claim that IPO companies are not required to be profitable any more, the data provides only slight support for this claim. Out of all non-IPO observations, 59 percent exhibit a ROA above 0. Out of IPO-firms on the other hand, only 55 percent are profitable at the end of their listing year.

The main dependent variable of the study, ROA, clearly requires transformations to become analyzable. In Table 4 I show three transformations of the ROA figure: winsoration at value ±10, logarithm and exponential. The negative ROA logarithms could be calculated by adding the figure 10 (as lowest case was winsorised to -10) to all of the cases. In Appendix 1 are the histograms for these variables. The histograms show that even though they resemble the normal curve much better than the unaltered ROA, there are still clearly problems with normality that could hinder their usability in regressions.

Table 4: ROA transformations

		ROAw	ln(ROA+10)	EXP ROA
N	Valid	99146	94716	99146
	Missing	210247	214677	210247
Mean		-.30	2.29	.93
Median		.03	2.31	1.03
Std. Deviation		1.37	.04	.30
Skewness		-5.19	-3.22	-1.45
Kurtosis		33.83	12.61	1.97
Minimum		-10.00	2.00	.00
Maximum		10.00	2.34	1.51
Percentiles	,1	-10.00	2.01	.00
	1	-10.00	2.09	.00
	10	-.72	2.25	.49
	25	-.16	2.29	.86
	50	.03	2.31	1.03
	75	.10	2.31	1.10
	90	.17	2.32	1.19
	99	.41	2.33	1.51
	99,9	2.05	2.34	1.51

ROAw = ROA winsorized at ±10, ln(ROA+10) = Natural logarith of ROA+10, EXP ROA = Exponent of ROA

Dealing with delistings

Companies that delist from the stock exchange during the period of my study are problematic for this study. If a delist is made due to bankruptcy, disregarding the delisted company after it ‘disappears’ from the data leads to an upward bias for the profitability, as in reality the company’s bondholders and stockholders most likely face highly negative profits in this situation. On the other hand, if the company delists due to being acquired or a similar situation, the bondholders generally face no changes in their profits, while the shareholders most likely gain highly positive profits during this financial year.

Macev et al. (2005) found that only 30% of delistings in NYSE and 12% in Nasdaq were bankruptcies during their study period. Beaver et al. (2005) found that on average, one year before bankruptcy ROA is -12%. In my sample the median is -6% and in bankruptcy year -11%, though only 539 and 116 cases, respectively, are available. Other interesting comparisons between the fundamentals of companies that are delisting the following year and the whole sample can be made. Stock valuation does not seem to help in forecasting the coming delisting, as the amount of PB > 1 firms is identical both pre-delist, in delist year (when data is available) and the whole sample, ~78%. The change in Total Assets seems to hint of the delisting, as it is 7% (median) in the subsample, but -2% one year before delisting and -4% in the year of the delist.

However, with my data the delisting dilemma does not seem to be very influential. Out of the subsample used in the analysis, only 12 of 32 168 firm years ended in a delisting. This amount is arguably so small, that it does not have any statistical effect how the delistings are handled. It is best not to make any harsh assumptions to either direction, and treat delistings passively.

4.3 Variables

The risk proxies used in the models are adapted from several former studies including profitability papers, credit risk and bankruptcy models. In addition, control variables are determined like in the majority of accounting and finance studies. To find out which variables measuring risk were suitable for building my model; I used the bankruptcy models of Demers and Joos (2007), Campbell et al. (2008), Nekrasov and Shroff (2009) and Shumway et al. (2001). Additionally I used the credit risk models of Baghai et al. (2010), Blume et al. (1998) and Altman and Sabato (2007).

The building of the model involved testing large numbers of variables to find the best variable describing a certain kind of risk and to find the best fit for the model. While most of the models use market-based variables such as volatility of share returns, I focus on the fundamentals only, with the exception of using year-end MarketCap. After a preliminary group of risk proxies that appear to be statistically significant in many occasions was formed, the actual regression model was formed by trying and finding the best fit from the variables. It is also important to assure that the variables selected measure different things, i.e. there is no excessive multicollinearity.

The variables can be divided into the following categories: profitability, financial risk, general business risk and control variables.

The dependent variable in the main regression is firstly ROA > 0 at year t+1 and secondly ROA>0 at t+3 years and t+5 years. Lie (2001) states that if ROA is forecasted for more than one year in the future, a potential problem emerges; statistical problems multiply compared to using one year forward ROA. This means that ROA at t+1 years should be the first test to be conducted, after which additional tests can be run to see if the results remain unchanged.

Table 5 summarizes the variables used in the statistical tests, what risk they measure, their expected coefficient sign in the regressions, how they were adjusted and the formula used to calculate them.

Table 5: List of variables

	Variable	Model	Exp. Sign	Risk	Note	Formula
Prof.	ROA > 0	P,C	+	Profitability	Dummy	ROA > 0
	ROA > 0 t+n			-	Dummy	ROA t+n > 0
	ROA_GROUP	P,C	+	Profitability	Ordinal [1-4]	ROA <25% Ind. = 1, 25%-0 = 2, 0-75% = 3, >75% = 4
	ROA_GROUP t+n			-	Ordinal [1-4]	ROA <25% Ind. = 1, 25%-0 = 2, 0-75% = 3, >75% = 4
	ROA_Change_1YRw	-	-	Growth	Winsorized @1%	(ROA t-1 – ROA t) / ROA t-1
	Profitmargin_w	-	+	Profitability	Winsorized @ [-2000, .99]	EBIT / Sales
	ROA_INDMED_POSnX	P,C	+	Ind. Relative	Dummy	2x= 2x IND. MED.ROA > ROA > 5x IND.MED.ROA
	ROA_INDMED_NEGnX	P,C	-	Ind. Relative	Dummy	15x = ROA < -15x IND.MED.ROA
	Div > 0 DUM	-	+	Profitability	Dummy	Dividends>0
General	DA/TA_w	-	+	Investment	Winsorized @1%	Depreciation&Amortization / Total Assets
	EBIT_STD_nYRSprior	-	-	Volatility	Calculated in Excel	Standard Deviation (EBIT t-1...EBIT t-5)
	LnSales	P,C	+	Size	Logarithm	Ln(Sales)
	S/TA_w	P,C	+	Effectiveness	Winsorized @1%	Sales / Total Assets
	AGE	P,C	+	Maturity	-	Year - Founding year
	Tassets_1YRchange_w	C	-	Growth	Winsorized @1%	(Total Assets t-1 - Total Assets t) / Total Assets t-1
	EBITDAtoTDebt_w5	C	+	Coverage	Winsorized @5%	(EBIT+Depreciation&Amortication) / TotalDebt
	P/B > 1 DUM	C	+	Valuation	Dummy	(MarketCap/Book value of Equity) > 1
Fin.	RE > 0 DUM	P,C	+ / -	Leverage	Dummy	Retained Earnings > 0
	STDebt/TDebt_w	C	-	Leverage	Winsorized @1%	Short-term Debt / Total Debt
	MCAP/TL_w	C	+	Leverage	Winsorized @1%	MarketCap / Total Liabilities
	CA/CL_w	C	+	Liquidity	Winsorized @1%	Current Assets / Current Liabilities
Control	DUMMY_n	P,C	N/A	Year	Dummy	Year dummy 1990-2010, 2006 as reference
	COUNTRYDUM_n	P,C	N/A	Country	Dummy	81 Country dummies, USA as reference

Other variables mentioned in Chapter 4.3 were either not found significant in any case, or lacked data for executing the tests. Winsorized @ 1% means winsoration at 1% lowest value and 99% highest value. P means Parsimonious, C means Comprehensive.

For some variables I used a method where the variable is transformed into a dummy, based on some 'natural' threshold value, usually 0, 1 or industry median value. In these cases the argument is that the value in itself is not so important, but the fact whether it exceeds some value that has been found crucial in former studies. The most obvious example is the case of ROA; whether the company becomes profitable or retains its profitability in the future, in other words whether ROA > 0. Namely this threshold in profitability is very important for many stakeholders, as it even has a large psychological meaning. Business press will write that a firm "remained profitable" in comparison to "made a loss" when operating profit is marginally above or below 0, respectively.

Reflecting back on the different components of fundamental risk determined in Chapter 2.2, variables measuring each component should be tested to see whether they have an effect on profitability. To measure the financial risk of a firm, variables measuring both short-term leverage (STD/TA) and long-term leverage (LTD/TA) have to be included. As high-techs, especially IPOs usually have a limited amount of debt in their balance sheets, a simple dummy telling whether the firm has any debt in its balance sheet could be informational. To measure the other side of financial risk, borrowing cost risk, a measure of *coverage* (e.g. EBITDA/Int. exp.) should be added. This is in accordance with Chapter 2.2, but it is more practical to use a coverage multiple than estimate RNOA and the interest rate as percentages and compare them.

The components of operating risk also require specific measures. Expense risk can be measured with the volatility of operating margin (EBIT/S). Similarly, operating leverage risk can be measured with the volatility of Fixed Costs/Sales. Asset turnover risk can be measured with volatility of S/TA, or alternatively in a more detailed way; volatility of sales and volatility of total assets separately. Volatility of sales also accounts for growth risk. Fama and French (2005) call the change in total assets investment. They found that "…current profitability is related to future investment, and that current investment is related to future profitability." If this is the case, to explain current profitability a measure of lagged asset growth can be used, and to explain future profitability a measure of current asset growth might prove useful.

Some models use dividend related figures such as dividend payout-ratio, dividend growth or simply a dummy of 'dividend paying' or not as indicators of future stock returns or profitability.

Static balance sheet figures can be expressed as averages between year beginning and year end values, as this gives a 'truer' picture of how the company looked like during the year. However, this somewhat reduces the amount of cases available, so I use year-end figures for balance sheet items.

4.3.1 Profitability

Profitability is used both as an independent variable and as a dependent variable. I argue that current profitability can be used as a measure of risk: an unprofitable company is riskier than a profitable one. As stated earlier, the profitability measure in this study is Return on Assets. In Qian and Li (2003) past profitability was positively associated with current profitability, but only significant on the 10% level.

Lie (2001) states the following: *"My regression results suggest that a model of expected future earnings should incorporate past levels of ROA, past changes in ROA, and market-to-book ratios."* By this argument, instead of using just the past profitability level, also the latest change in profitability should be used to take into account either persistence or mean-reversion of profitability, whichever be prominent in that situation. In addition, P/B can exhibit investors' knowledge about the future development in the company's fundamentals. Lie (2001) also stresses the importance of dividing the sample firms on the basis of whether their ROA, $\Delta ROA_{t,t+1}$ and P/B are above or below median values or, in the case of P/B, above 1.

Due to the highly skewed and heteroskedastic nature of the data, unaltered ROAs cannot be used as a measure of profitability either as dependent or explanatory variables. I tried several kind of alterations for ROA. First I winsorized ROA to 1% and 99% values. Seeing that the distribution still remained very peculiar due to the numerous outliers, I tried both logarithmic and exponential (with truncating) changes, after which the distributions look much 'neater', but still do not follow the normal distribution. See Appendix 2 for the descriptives and histograms.

As current ROA is the most important explanatory variable of future ROA, so it is interesting to also try separately using its components, as defined earlier, for potentially increasing the variable's explanatory power or getting more information about the underlying nature of the earnings logic. In accordance with the DuPont model, the components of ROA, Profit margin and asset turnover can be used as explanatory variables in regressions instead of ROA. Another possibility is using cash flow and accrual components as determined by Sloan (1996). However, the data places its restrictions on using both of these alterations, as simple ROA is available for many more firms than its different components, which might hinder the reliability of the analysis.

The following argument by Lie (2001) justifies also the creation of another variable; ROA change from year t-1:
"I find that future changes in performance are negatively related to past levels and negatively related to changes over the past year. The exception is when performance is high but declining. In those cases, future changes in performance are positively related to past changes (i.e., there is a momentum effect rather than a reversion effect). I find that future changes are positively related to market-to-book ratios, except when past level of performance is low and the market-to-book ratio is high. These results indicate that future changes in performance are partially predictable. Therefore, researchers should control for this predictable portion as they attempt to assess what portion of future changes is unexpected."

To test the claim about profitability's mean reversion towards the industry median, as presented by Fama and French (2000), I undertake, on an ad-hoc basis, procedures specifically tailored for this kind of highly leptokurtic and skewed data. I partly follow measures Lie (2001) used in his study:

"Alternatively, the results in Burgstahler and Dichev (1997) suggest that managers are more likely to temporarily manipulate earnings upward than downward, suggesting that earnings reversion is more likely to take place following an increase in earnings than following a decrease. To uncover some of these complex relations, I partition my sample into eight groups, based on whether the ROA in year t and the change in ROA from year t-1 to year t

are above or below the median, and whether the market-to-book ratio is above or below one.”

I create 8 dummies measuring how far a company’s profitability is from the industry median. A simple industry deviance variable cannot be used here, as it would be completely correlated with the year t ROA figure that is already included as the basis of the models. As reliable industry medians are hard to come by, I calculated annual medians from my sample to use as a proxy for industry median. The dummies are named ROA_INDMED_POS/NEG_nX, where N is 2, 5, 10 or 15 medians away from the sample median. The different levels of dummies are designed to account for Fama and French’s (2000) claim that larger deviances in either direction should revert to industry mean faster. Such large deviances (up to 15 times industry median) are due to the nature of the data, where median is constantly small and positive, but standard deviations are large and increasing with time. A case can only belong in one group at a time. To clarify, e.g. ROA_INDMED_POS2X includes companies with ROA at least 2 times industry median of year t, but less than 5 industry medians. ROA_INDMED_NEG15X includes companies whose ROA is at least -15 times industry median, i.e. the very ‘worst’ group of companies. Companies between 2 and -2 times industry median do not belong in any of these groups, eliminating the multicollinearity problem of dummies.

From the sample of 42 627 firm years used in the Comprehensive model (defined later), 31% are near industry profitability and get a value of 0 for all dummies. A large portion, 26% of firms are at least two medians above (non-cumulatively), while 7% are two medians below industry profitability. 12% are at least 5 medians above and 6% are below 5 times industry median. Next is a change of frequency between negative and positive deviances, as 6% of firms are negatively, but only 3% positively deviated from 10 industry medians. Similarly, 3% belong in the most deviated negative dummy, while 2% are in the positive side.

IPOs are not treated separately in this context, but each IPO can belong in an INDMED group as well as any other company; the relative profitability is not compared to other IPOs exclusively, as I believe IPOs are ‘competing’ against other companies, not only other IPOs.

I also calculated the deviance from industry median profitability in a slightly simpler way to make sure there is no problem associated with using such dummies that would be hidden by the complexity of the 8-step dummies. Firstly two dummies, representing whether a company has positive or negative profitability at year t, are created. The dummies are then multiplied by the deviance from industry variable, so that a company always gets a value in either the positive deviance dummy or negative deviance dummy. This second way of calculating industry deviance returns similar results as the one reported in my regression results.

Dividends

The signaling theory states that firms use dividends to inform about their future prospects. Fama and French (2001) verify that companies that pay dividends are on average more profitable than those who do not. Additionally, those companies that have paid dividends before, but have stopped paying them have the lowest profitability. This is logical, since stock markets react so strongly to diminishing dividends that companies surely avoid decreasing them to the very last moment. The study also found that larger firms are more prone to paying dividends, but this is controlled by the LnSales variable on my study. Pastor and Veronesi (2003) present an opposing view: firms with low expected profitability 'pay out' their equity as dividends and similarly when expected profitability is high, firms reduce dividends to finance their investments. However, it seems probable that the amount of dividends is of secondary importance, so a simple dummy describing whether the firm has dividends > 0 during year t seems sufficient in capturing this potential notion about the firm's future prospects, similarly as in Fama and French (2000).

However, high-tech IPOs are very unlikely to pay dividends (only 12.33% of total 10 517 IPOs reported dividends, while 27.88% of 88 629 non-IPO firms whose ROA could be calculated were paying dividends) so their informative value is expected to be low. In addition, despite using several tests, Grullon et al. (2005) find no predictive power in dividend change metrics when controlling for non-linearities in earnings.

Earnings growth and volatility

Like mentioned earlier, earnings growth is seen as risky by investors. Earnings volatility is similarly seen as a negative thing, as the higher the volatility, the higher the chance of negative earnings. The earnings growth variable is calculated as a cumulative figure for 3 and 5 years growth. Earnings volatility is the standard deviation of 3 or 5 years past earnings.

4.3.2 General business risk

This chapter includes the variables which I have named general business risk variables, i.e. which do not measure either profitability nor financial risk. A size variable should be included in the models for two reasons. The main reason in the context of this study is to measure 'size risk'. It is often claimed that smaller companies are riskier than larger, more established ones. E.g. Fama and French (1995) have found that smaller firms (measured by market cap) are usually less profitable. The other reason is to control for the effect of size and to isolate other variables' effects better. Usually three options (often their ln-transformations to reduce the effect of outliers) can be used as the size variable: Sales, Total Assets and Market Capitalization. These items are included in several other variables, but I decided LnSize would be the best one to signal company size in the high-tech sample. After an IPO, these companies can have a large, arguably bloated, balance sheet and high market capitalization, so sales should better hint about business development. Demers and Joos (2007) use LnSize to signal about *"establishment in product markets"* for IPOs. The ln-transformation is required to control for the numerous outliers. Also an age-variable is required to capture various effects of age in firms. Pastor and Veronesi (2003) state that younger firms are on average more profitable and have higher stock valuations than older, otherwise similar firms have. However, in Qian and Li (2003) the coefficient for age was positive, but not statistically significant.

Price-to-Book

For example Fama and French have used market-to-book in many of their studies for forecasting future stock returns. Although this study does not focus on stock market data, it is interesting and statistically simple to test a theoretical (calculated only with year-end prices annually) market-to-book multiple. A multiple like this is not very reliable, but it can be used to see if the stock market (lagged) possesses some information about future profitability that is not readable from the financial statements. Fama and French (2005) also state that low B/M (i.e. high P/B) firms "tend to be more profitable". This also variable also 'completes' Lie's (2001) method mentioned above. Barron et al. (2002) used P/B as a control variable for growth opportunities, i.e. they believe that the market has information about the future earnings of firms. Pastor and Veronesi (2003) state that high P/B is associated with uncertainty about future profitability.

Operating leverage

Operating leverage can be measured with a simple Fixed Assets/Total Assets variable. However, the data for this was very scarcely available in the databases, and it is expected that the amount of Fixed Assets for the high-techs is quite small as most of the assets are intellectual.

Depreciations/Accruals

Fama and French (2000) used a measure of depreciation as a proxy of capital intensity, but found no explanatory power for profitability. Sloan (1996) reports that the accrual component of earnings is less persistent than cash flows, so a high proportion of accruals in earnings should show as lower future earnings. I argue that Depreciation/Total Assets can be used as a proxy of this, as it is more widely available than accruals. In this case Depreciation should be positively correlated with future returns, as depreciations reduce the amount of total accruals. The effect of depreciation is not expected to be large, as high-tech companies do not widely invest in tangible assets which would require depreciations to be made. Other accrual components are largely already included in other variables of my models. The creation of an extensive Accruals variable would require time and resources beyond the scope of this study. One relatively simple way would be to construct a dummy for certain level of CFO/EBIT as per Barber and Lyon (1996).

Investment

Change in Total Assets is used as a proxy for investment in Fama and French (2005). They found that asset growth is negatively correlated with future profitability when size and other fundamentals are controlled for. Similarly, in Fairfield et al. (2003) growth in long-term net operating assets has a negative correlation with future ROA, and I argue that the effect should be similar with a simpler Total Assets growth variable. The advantage of using asset growth instead of a figure such as Capital Expenditure (e.g. Beneish et al.), is that Total Assets are very widely available for most firms, unlike CAPEX or similar figures.

Research & Development Costs

R&D is often thought to be an important success factor especially for high-techs. R&D/Sales variable is often used in comparing technology companies, so I constructed that variable for my tests too. However, since all of the sample companies are high-tech firms that have high R&D expenses, large differences inside the sample are not expected to be found with this variable. Qian and Li (2003) used R&D intensity as a measure of 'Innovator position' and found a highly significant positive relationship between it and profitability.

4.3.3 Financial risk

The following variables measure financial risk in one way or another. It would be ideal to construct a dummy to capture the adverse effect of having both high financial risk and high operational risk. However, business risk is not easy to measure and not necessarily shown in the financial statements.

Leverage

Leverage was discussed in Chapter 3.3. Leverage figures as such are not expected to have a large effect on profitability in this sample. The earlier literature on leverage's effect on profitability is quite mixed. Qian and Li (2003) found a minor positive relationship, but it is not statistically significant. The variable I constructed for this study is Marketcap divided by Total Debt.

Debt Maturity

As mentioned earlier, it is not only important how much leverage a firm has, but how it comprises of short-term and long-term debt. What has been found to be increasing risk is namely short-term debt. The variable STDebt/TDebt shows the ratio of short term debt, 'debt maturity' in the balance sheet. This ratio is expected to have a negative relationship with future profitability. In this study, short term debt includes the current portion of long term debt.

Liquidity

CA/CL can be used as a simple measure of liquidity. However, it is not expected to have a strong effect in the high-tech sample, as the amounts of both Current Assets and Current Liabilities are relatively low in these companies.

Retained earnings

In accordance with Bhattacharya et al. (2010), it is interesting to see if negative retained earnings, or in other words accumulated deficits and thus the increased failure risk of a firm transform into lower future profitability. On the other hand by Demers and Joos (2007) accumulated deficits should translate into higher future profitability. I created a dummy variable for Retained Earnings > 0 (RE > 0), which should be accurate enough to see if has predictive power. I argue this dummy can be used as well for mature companies as IPOs.

4.4 Model

The aim of the study is to find out if risk proxies can be useful in forecasting profitability for high-tech companies. I expect that a new model can be developed on ad-hoc basis by seeing what kind of variables in the existing models are the most influential. This new model can provide useful information for investors about the future profitability of high-tech companies, which is crucial in making investment decisions. In order to find support or reject Hypothesis 1, several of the independent variables should be found statistically significant, and preferably have similar signs in relation to measured riskiness.

In total, four kinds of regression models are built and tested on the sample: binary logit, ordinal logit, multinomial logit and linear OLS. The primary model explains future profitability (t+1, t+3, t+5 years) with risk proxies. The main motivation for using also 3 and 5 years is to see if different variables remain significant for longer periods, and if some of them even become relatively more useful when the timeframe is increased. To clarify, a single test always uses year t explanatory variables in explaining year t+n profitability.

Two types of models are created for each type of regression used in the study: firstly Parsimonious model that does not use lagged variables and does not have a large amount of explanatory variables. Secondly, Comprehensive model that includes lagged variables and a more thorough selection of financial statement figures is constructed. Table 5 reports which variables belong to both models and which belong only to the Comprehensive one. To find support for Hypothesis 3, the Comprehensive models should have significantly higher explanatory power.

The main challenge of selecting the variables to use in the model is the trade-off between increased informativeness and loss of observations and thus reliability and generalization potential. The more lagged variables are used in explaining future profitability, the smaller the effective sample size will be, due to limitations in available data. In absolute numbers my sample is large enough to provide statistically significant results even when only a small fraction of observations is used, but there is a large risk of the formation of some kind of bias in the results, as only certain kind of companies are included in the analysis. Most likely only larger and more followed companies have detailed information about lagged variables available. Additionally, the comparison between IPOs and mature companies is impossible, if e.g. historical volatility figures are used, as IPOs have no historical pre-IPO data available. For this reason, IPOs are tested only with the Parsimonious model, which is then compared to the all-sample results. Country and year dummies are included in my regressions, but sub-industry dummies are excluded. For country dummies the reference group is the largest group; US companies. For year dummies, the reference year is the year with the largest amount of observations; 2006 for 1YR and 3YR models and 2004 for 5YR models.

Various kinds of sensitivity analyses are conducted to make sure that the obtained results are not biased in any way and depend only on a single variable or characteristic. Instead of ROA, ROE was used to see if the results applied to the equity holder too. This was confirmed by preliminary tests. It was also tested whether excluding current ROA from the regression models makes the results completely insignificant. This did not happen, and it is clear that the other variables in the models are also important. While year dummies are included in the regression, the models were still tested with a single year sample to see if the results remain unchanged, which is what happened.

Binary logit model

The main regression of the study is the binary logit model.

Binary logistic models measure the odds of a certain event happening, in this case the event of "profitability", defined here simply as ROA > 0. The model coefficients show the log-odds of specific variables for this event. When the exponent of these log-odds is taken, odds are obtained, which in turn can be interpreted to see how much a certain value of a variable influences the probability of profitability. The main binary logit model is described below:

$$Prob(ROA_{t+n} > 0) = \frac{1}{1+e^{-z}} \text{, where}$$
$$z = \beta_0 + \beta_1(ROA_t > 0) + \beta_2(RE > 0) + \beta_3 lnSales + \beta_4 S/TA + \beta_5 AGE + \sum \beta_j INDMED + \sum \beta_t YEAR + \sum \beta_k COUNTRY \tag{5}$$

Where $ROA_{t+n} > 0$ is the a dummy for Return on Assets for year $t+n$, β_0 is the regression intercept, β_n are the respective regression coefficients, RE > 0 is the dummy for retained earnings, lnSales is the logarithm of annual sales, S/TA is Sales divided by Total Assets, INDMED are the industry median deviance dummy variables, YEAR are year dummies and COUNTRY are country dummies where k is the specific country.

The main motivation for using binary logit regression here is the fact that the common OLS-regression does not 'work' with this dataset, as explained below in detail. The zero point of profitability is also interesting for several reasons. When a company exceeds it, its operations can be said to be economically sustainable at least in the short run, as it is creating value instead of destroying it.

The models will be run first on the whole sample, after which they will compared to the limited sample of IPO firms. Potentially binary logit regression could be used also for explaining very high profitability, e.g. ROA > (90% sample ROA).

Ordinal logit model

The ordinal logit model is used to extract additional information from the sample and for sensitivity analysis of the results of binary logit models. In comparison to the binary logit regression described above, ordinal logit regression can provide much more detailed information about the future profitability of firms and the effect of fundamental risk. It is possible and even probable that some risk factors not only affect whether a company becomes profitable, but whether it either has a very low future profitability, or on the other hand a very high future profitability.

I first created 3 classes of profitability; First Quarter in relation to sample, Second to Third Quarter and Fourth Quarter, but decided to split the largest 'middle group' into two, based on the natural split point of zero. This leaves the four profitability groups as: 1Q (<25% ROA), 2-3QA (25%-0), 2-3QB (0-75%) and 4Q (>75%). The latter group is used as the reference group in my models. This division should offer more information and easier comparability to the results of the binary logit models. The relative profitability classes provide also interesting information for investors. It can be argued that not always the key point of interest is profitability as an absolute figure, but relative profitability in comparison to the industry. Industries' profitability has large fluctuations over time and economical situations, but if an investment is made to a company that is constantly among the most profitable among its industry, the investor will most likely be satisfied with their investment.

The models created can have different abilities to predict good or bad (relative to industry) performance, which have to be taken into account when analyzing the results. Parsimonious models with a few independent variables will be compared to Comprehensive models with more fundamental variables as explanatory variables. In addition, models will be tested both with the whole sample, as well as limiting the sample to only IPO companies.

Multinomial logit model

Results from ordinal logit model indicate that there might be problems with the statistical reliability with those results, e.g. the potential violations in the assumption of proportional odds (or parallel lines), meaning that the model's coefficients differ in different thresholds of the sample. This is why multinomial logit model is needed to verify whether those conclusions hold. The same profitability classes are used for the multinomial model as for ordinal models. Multinomial logit regression calculates separate coefficients for each class of the dependent variable in comparison to the reference class, in this case Q4; the most profitable firms. When using multiple logit regression, some information is 'lost' in comparison with ordinal regression, as the order of the classes is not taken into account.

The output of multinomial regression is hardest to interpret. Here the coefficients in the regression output mean how much more/less a company is likely to belong in Group N (1, 2, 3) in comparison to the most profitable Group 4. This means that the coefficients have to be analyzed separately in all of the profitability classes (4Q is excluded as a reference class by default, and it assumes coefficients of 0). As in the other models, the IPO sample will be analyzed with Multinomial regression as well.

Linear OLS-model

Linear Ordinary Least Square regression is usually the primary method of analysis in accounting and finance research. However, sometimes the nature of the data or research problem motivates the use of other regression methods.

I tried forming various Linear OLS-models, but numerous statistical problems cause all of them to be statistically unreliable. As an example of this, I attach the output of this regression function (Appendix 2). Though the model seems to have a relatively high R^2, acceptable Durbin-Watson and ANOVA, and the variables are statistically significant, the P-P Plot and Scatter plot show that the regression residuals are not nearly normally distributed, which ultimately means that the regression coefficients are biased and cannot be trusted.

The data is very heteroskedastic, resulting from skewness and leptokurtosis of most of the variables and a large amount of outliers. See Appendix 2 for the P-P Plots and scatterplots, which clearly demonstrate this. The P-P Plot should follow the middle axis relatively tightly, but now there are large deviations on both ends, even a mild inverted S-shape. The scatter plot on the other hand shows that the majority of residuals are concentrated in a restricted area, and the plot is not completely random. The regression residuals are not nearly normally distributed no deep conclusions can be made based on the OLS regression output. For this reason, OLS-regression in my study is used primarily for detecting multicollinearity among the variables and secondarily for using stepwise method to create the best set of variables for my Comprehensive models. This is done because there is a countless amount of fundamental factors that could affect profitability and additionally countless ways to measure those them. However, some of the variables were tested separately, but turned out insignificant in all tests, so they are left unreported.

5. Empirical results

In this section I firstly present the descriptive statistics for the sample. Secondly, correlations between variables used in the regressions are presented. Thirdly, regression outputs for binary and ordinal logistic regressions are shown. After that the results of the regressions are discussed.

5.1 Descriptive statistics

Table 6: Profitability variables used in models

	Valid	Missing	Mean	Median
ROA > 0	42627	0	.65	1
ROA > 0 t+1	37648	4979	.66	1
ROA > 0 t+3	28035	14592	.66	1
ROA > 0 t+5	20018	22609	.68	1
ROA_GROUP	42627	0	2.07	2
ROA_GROUP t+1	37687	4940	2.08	2
ROA_GROUP t+3	28117	14510	2.09	2
ROA_GROUP t+5	20018	22609	2.10	2

Table 7: Continuous variables used in models

	Mean	Median	Std. Deviation	Percentiles					
				1	10	25	50	75	99
LnSales	4.51	4.50	2.31	-1.94	1.79	3.18	4.50	5.89	10.28
S/TA_w	0.97	0.80	0.77	0.02	0.25	0.48	0.80	1.23	4.50
AGE	24.79	18.00	21.98	1.00	6.00	10.00	18.00	32.00	101.00
TA_1YRchange_w	0.24	0.07	0.96	-0.68	-0.23	-0.06	0.07	0.25	4.79
EBITDA/TDebt_w5	1.16	0.34	5.96	-13.70	-1.99	-0.04	0.34	1.17	19.67
Profitmargin_w	-0.39	0.04	1.75	-10.00	-0.68	-0.07	0.04	0.12	0.66
STDebt/TDebt_w	0.47	0.42	0.37	0.00	0.00	0.13	0.42	0.85	1.00
MCAP/TL_w	5.49	2.05	12.51	0.06	0.40	0.88	2.05	4.96	60.49
CA/CL_w	2.66	1.68	3.81	0.00	0.64	1.11	1.68	2.74	23.46

Table 8: Dummy variables used in models

Variable	Mean	Median	Std. Deviation
P/B > 1 DUM	.78	1	0.42
RE > 0 DUM	.58	1	0.49
ROA_INDMED_POS2X	.26	0	0.44
ROA_INDMED_POS5X	.12	0	0.33
ROA_INDMED_POS10X	.03	0	0.16
ROA_INDMED_POS15X	.02	0	0.13
ROA_INDMED_NEG2X	.07	0	0.25
ROA_INDMED_NEG5X	.06	0	0.23
ROA_INDMED_NEG10X	.03	0	0.18
ROA_INDMED_NEG15X	.10	0	0.30

5.2 Correlations

Table 9: Spearman correlations between ROA > 0 and independent variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	**ROA > 0**	-	,578**	,407**	,350**	,476**	,419**	,117**	,182**	,324**	,737**	,824**	,023**	-,047**	,018**	,052**
2	**ROA > 0 t+1**	,578**	-	,456**	,371**	,392**	,393**	,152**	,183**	,190**	,512**	,580**	.007	-,032**	-,037**	.004
3	**ROA > 0 t+3**	,407**	,456**	-	,460**	,313**	,365**	,151**	,186**	,081**	,374**	,418**	-,026**	-,028**	-,087**	-,027**
4	**ROA > 0 t+5**	,350**	,371**	,460**	-	,286**	,350**	,128**	,185**	,064**	,317**	,366**	-,030**	-,029**	-,094**	-,044**
5	**RE > 0 DUM**	,476**	,392**	,313**	,286**	-	,421**	,071**	,189**	,161**	,428**	,469**	-,082**	-,028**	,037**	,131**
6	**LnSales**	,419**	,393**	,365**	,350**	,421**	-	,210**	,339**	,070**	,361**	,398**	.009	-,113**	-,159**	-,084**
7	**S/TA_w**	,117**	,152**	,151**	,128**	,071**	,210**	-	,158**	-,182**	,189**	-,020**	-,033**	,170**	-,252**	-,127**
8	**AGE**	,182**	,183**	,186**	,185**	,189**	,339**	,158**	-	-,078**	,155**	,142**	-,109**	-.005	-,191**	-.006
9	**TA_1YRchange_w**	,324**	,190**	,081**	,064**	,161**	,070**	-,182**	-,078**	-	,269**	,373**	,127**	-,151**	,204**	,098**
10	**EBITDA/TDebt_w5**	,737**	,512**	,374**	,317**	,428**	,361**	,189**	,155**	,269**	-	,768**	,032**	.006	,190**	,172**
11	**Profitmargin_w**	,824**	,580**	,418**	,366**	,469**	,398**	-,020**	,142**	,373**	,768**	-	,087**	-,110**	,144**	,094**
12	**P/B > 1**	,023**	.007	-,026**	-,030**	-,082**	.009	-,033**	-,109**	,127**	,032**	,087**	-	-,112**	,425**	-,036**
13	**STDebt/TDebt_w**	-,047**	-,032**	-,028**	-,029**	-,028**	-,113**	,170**	-.005	-,151**	.006	-,110**	-,112**	-	-,133**	-,234**
14	**MCAP/TL_w**	,018**	-,037**	-,087**	-,094**	,037**	-,159**	-,252**	-,191**	,204**	,190**	,144**	,425**	-,133**	-	,463**
15	**CA/CL_w**	,052**	.004	-,027**	-,044**	,131**	-,084**	-,127**	-.006	,098**	,172**	,094**	-,036**	-,234**	,463**	-

* denotes significance at the 0.01 level, ** denotes significance at the 0.05 level

Table 10: Spearman correlations between ROA_GROUP and independent variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	**ROA_GROUP**	-	,641**	,470**	,396**	,426**	,379**	,131**	,152**	,327**	,724**	,790**	,068**	-,071**	,133**	,107**
2	**ROA_GROUP t+1**	,641**	-	,527**	,436**	,366**	,355**	,170**	,152**	,196**	,556**	,613**	,059**	-,059**	,078**	,056**
3	**ROA_GROUP t+3**	,470**	,527**	-	,534**	,298**	,322**	,156**	,148**	,099**	,428**	,469**	,038**	-,058**	,029**	,022**
4	**ROA_GROUP t+5**	,396**	,436**	,534**	-	,261**	,302**	,141**	,152**	,087**	,370**	,406**	,024**	-,062**	,001	,001

Independent variables numbered as in Table 9. * denotes significance at the 0.01 level, ** denotes significance at the 0.05 level

5.3 Regression output

On the next pages are reported the regression output for the empirical tests:

Table 11: Binary logit models for the whole sample
Table 12: Binary logit models for IPO sample
Table 13: Ordinal logit models for the whole sample
Table 14: Ordinal logit models for IPO sample

Multinomial logistic regression results are reported in Appendix 4.

Year or Country dummies are included, but not reported with any models.

I use a significance limit of 5% for p-values like the majority of studies in this field.

Table 11: Binary logit model output, whole sample

Model	Comprehensive 1YR		Parsimonious 1YR		Comprehensive 3YR		Parsimonious 3YR		Comprehensive 5YR		Parsimonious 5YR	
Variable	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
ROA > 0	1.087	0.000	1.109	0.000	.499	0.000	.508	0.000	.265	0.000	.269	0.000
RE > 0 DUM	.391	0.000	.386	0.000	.259	0.000	.268	0.000	.226	0.000	.233	0.000
LnSales	.189	0.000	.199	0.000	.208	0.000	.222	0.000	.215	0.000	.222	0.000
S/TA_w	.153	0.000	.166	0.000	.104	0.000	.128	0.000	.074	0.008	.079	0.002
AGE	.004	0.000	.004	0.000	.005	0.000	.006	0.000	.005	0.000	.005	0.000
Tassets_1YRchange_w	-.034	0.038			-.101	0.000			-.037	0.051		
EBITDA/TDebt_w	.019	0.000			.012	0.000			.006	0.087		
Profitmargin_w	.000	0.884			.000	0.349			.000	0.278		
P/B > 1 DUM	.091	0.019			-.043	0.320			-.053	0.287		
STDebt/TDebt_w	-.100	0.031			-.184	0.000			-.155	0.006		
MCAP/TL_w	-.002	0.145			-.002	0.065			-.001	0.597		
CA/CL_w	-.009	0.034			-.009	0.041			-.006	0.310		
ROA_INDMED_POS2X	1.010	0.000	1.046	0.000	.599	0.000	.607	0.000	.427	0.000	.427	0.000
ROA_INDMED_POS5X	1.319	0.000	1.384	0.000	.825	0.000	.840	0.000	.699	0.000	.701	0.000
ROA_INDMED_POS10X	1.369	0.000	1.456	0.000	.899	0.000	.921	0.000	.680	0.000	.688	0.000
ROA_INDMED_POS15X	.899	0.000	1.001	0.000	.375	0.002	.408	0.001	.349	0.007	.361	0.005
ROA_INDMED_NEG2X	-.284	0.000	-.306	0.000	-.075	0.299	-.088	0.224	-.173	0.052	-.184	0.038
ROA_INDMED_NEG5X	-.626	0.000	-.670	0.000	-.315	0.000	-.345	0.000	-.276	0.003	-.301	0.001
ROA_INDMED_NEG10X	-.655	0.000	-.722	0.000	-.422	0.000	-.460	0.000	-.291	0.008	-.327	0.002
ROA_INDMED_NEG15X	-.880	0.000	-.958	0.000	-.665	0.000	-.701	0.000	-.631	0.000	-.665	0.000
Constant	-1.684	0.000	-1.737	0.000	-1.386	0.000	-1.663	0.000	-1.078	0.000	-1.251	0.000
Nagelkerke R^2	0.505		0.504		0.344		0.341		0.298		0.297	
N	32292		32292		24031		24031		16936		16936	

Table 12: Binary logit model output, IPO sample

Model Variable	Parsimonious IPO 1YR Coeff.	Parsimonious IPO 1YR Sig.	Parsimonious IPO 3YR Coeff.	Parsimonious IPO 3YR Sig.	Parsimonious IPO 5YR Coeff.	Parsimonious IPO 5YR Sig.
ROA > 0	.921	0.000	.409	0.042	.154	0.544
RE > 0 DUM	.451	0.000	.270	0.026	.272	0.053
LnSales	.227	0.000	.213	0.000	.286	0.000
S/TA_w	.202	0.002	.098	0.100	.008	0.909
AGE	.014	0.008	.010	0.026	.013	0.012
ROA_INDMED_POS2X	1.026	0.000	.683	0.000	.301	0.075
ROA_INDMED_POS5X	1.392	0.000	.770	0.000	.806	0.000
ROA_INDMED_POS10X	2.297	0.000	1.104	0.000	.933	0.001
ROA_INDMED_POS15X	1.804	0.000	.723	0.005	.666	0.017
ROA_INDMED_NEG2X	-.600	0.007	.038	0.872	.043	0.882
ROA_INDMED_NEG5X	-.993	0.000	-.529	0.033	-.196	0.499
ROA_INDMED_NEG10X	-1.931	0.000	-.627	0.032	-.132	0.677
ROA_INDMED_NEG15X	-1.395	0.000	-.669	0.004	-.262	0.325
Constant	-1.753	0.000	-1.548	0.000	-1.336	0.000
Nagelkerke R^2	0.629		0.376		0.316	
N	3707		2963		2246	

Table 13: Ordinal logit model output, whole sample

Model	Comprehensive 1YR		Parsimonious 1YR		Comprehensive 3YR		Parsimonious 3YR		Comprehensive 5YR		Parsimonious 5YR	
Variable	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
[ROA_GROUP_nYRforward = 1]	-2.682	0.000	-2.743	0.000	-1.297	0.000	-1.221	0.000	-1.257	0.000	-1.172	0.000
[ROA_GROUP_nYRforward = 2]	-1.128	0.000	-1.192	0.000	-.058	0.505	.013	0.860	-.108	0.320	-.026	0.786
[ROA_GROUP_nYRforward = 3]	1.753	0.000	1.685	0.000	2.213	0.000	2.282	0.000	2.046	0.000	2.125	0.000
RE > 0 DUM	.325	0.000	.323	0.000	.277	0.000	.278	0.000	.246	0.000	.247	0.000
LnSales	.153	0.000	.158	0.000	.168	0.000	.177	0.000	.173	0.000	.181	0.000
S/TA_w	.122	0.000	.123	0.000	.087	0.000	.093	0.000	.053	0.015	.049	0.019
AGE	.002	0.001	.002	0.005	.002	0.000	.002	0.001	.003	0.000	.003	0.000
Tassets_1YRchange	2.049E-05	0.379			.021	0.000			.014	0.000		
EBITDA/TDebt_w	.025	0.000			.000	0.332			.000	0.579		
Profitmargin_w	.001	0.060			.004	0.896			-.005	0.903		
P/B > 1 DUM	.048	0.104			-.178	0.000			-.194	0.000		
STDebt/TDebt_w	-.111	0.001			-.009	0.009			-.009	0.052		
MCAP/TL_w	.000	0.821			2.293E-05	0.301			2.057E-05	0.351		
CA/CL_w	-.005	0.133			-.002	0.031			.000	0.898		
ROA_INDMED_POS2X	.708	0.000	.735	0.000	.455	0.000	.475	0.000	.279	0.000	.292	0.000
ROA_INDMED_POS5X	1.267	0.000	1.316	0.000	.705	0.000	.737	0.000	.435	0.000	.458	0.000
ROA_INDMED_POS10X	1.319	0.000	1.395	0.000	.791	0.000	.835	0.000	.554	0.000	.590	0.000
ROA_INDMED_POS15X	1.274	0.000	1.376	0.000	.559	0.000	.621	0.000	.427	0.000	.479	0.000
ROA_INDMED_NEG2X	-.143	0.009	-.172	0.002	.003	0.964	-.026	0.691	-.069	0.373	-.087	0.259
ROA_INDMED_NEG5X	-.178	0.009	-.227	0.001	-.092	0.217	-.153	0.039	-.225	0.007	-.264	0.002
ROA_INDMED_NEG10X	-.310	0.000	-.391	0.000	-.174	0.057	-.264	0.004	-.188	0.070	-.247	0.016
ROA_INDMED_NEG15X	-.722	0.000	-.831	0.000	-.481	0.000	-.585	0.000	-.578	0.000	-.652	0.000
[ROA_GROUP=1]	-3.240	0.000	-3.354	0.000	-1.636	0.000	-1.725	0.000	-1.101	0.000	-1.162	0.000
[ROA_GROUP=2]	-2.300	0.000	-2.376	0.000	-1.042	0.000	-1.094	0.000	-.779	0.000	-.813	0.000
[ROA_GROUP=3]	-1.517	0.000	-1.567	0.000	-.804	0.000	-.837	0.000	-.640	0.000	-.660	0.000
[ROA_GROUP=4]	0		0		0		0		0		0	
Nagelkerke R^2	0.558		0.556		0.351		0.348		0.286		0.284	
N	32168		32168		23974		23974		16850		16850	

The top row ROA_GROUP variables report the intercept for the respective threshold. The bottom ROA_GROUPs report the coefficients in relation to Group 4.

Table 14: Ordinal logit model output, IPO sample

Model	Parsimonious IPO 1YR		Parsimonious IPO 3YR		Parsimonious IPO 5YR	
Variable	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
[ROA_GROUP_nYRforward = 1]	-2.125	0.000	-.489	0.032	-.192	0.536
[ROA_GROUP_nYRforward = 2]	-.625	0.004	.686	0.003	.962	0.002
[ROA_GROUP_nYRforward = 3]	1.885	0.000	2.495	0.000	2.826	0.000
RE > 0 DUM	.458	0.000	.270	0.008	.353	0.003
LnSales	.190	0.000	.213	0.000	.234	0.000
S/TA_w	.067	0.145	.013	0.786	-.077	0.166
AGE	.006	0.089	.005	0.126	.005	0.186
ROA_INDMED_POS2X	.517	0.000	.384	0.003	.314	0.036
ROA_INDMED_POS5X	1.158	0.000	.620	0.001	.842	0.000
ROA_INDMED_POS10X	1.923	0.000	.854	0.001	.965	0.001
ROA_INDMED_POS15X	1.721	0.000	.850	0.001	1.179	0.000
ROA_INDMED_NEG2X	-.410	0.027	.106	0.612	-.040	0.871
ROA_INDMED_NEG5X	-.747	0.000	-.447	0.043	-.260	0.303
ROA_INDMED_NEG10X	-.976	0.000	-.285	0.290	-.408	0.180
ROA_INDMED_NEG15X	-1.267	0.000	-.388	0.158	-.335	0.288
[ROA_GROUP=1]	-2.637	0.000	-1.383	0.000	-.226	0.509
[ROA_GROUP=2]	-1.860	0.000	-.681	0.003	-.009	0.974
[ROA_GROUP=3]	-1.251	0.000	-.491	0.000	-.056	0.735
[ROA_GROUP=4]	0		0		0	
Nagelkerke R^2	0.623		0.374		0.291	
N	3693		2950		2239	

The top row ROA_GROUP variables report the intercept for the respective threshold. The bottom ROA_GROUPs report the coefficients in relation to Group 4.

5.4 Discussion

In the following results discussion, ceteris paribus is expected, unless otherwise stated. With the binary models I talk about *likeliness of future profitability* (ROA > 0), while for ordinal and multinomial logistic models the dependent variable is the *relative profitability class* in comparison to the sample. This means that profitability as an absolute figure will primarily not be discussed.

5.4.1 Main tests

Current profitability

When we look at the coefficients in 1-5YR models, we see that the effect of currently having ROA > 0 on future probability of having ROA > 0 is positive and significant in all models, but it diminishes when the timeframe is increased. For the 1YR model companies with positive ROA are 1.85 times more likely to be profitable during the next year than companies with negative ROA. For 3YR and 5YR models, the odds-ratios are 0.63 and 0.38, respectively. These are expected results, as it is only logical that current profitability is a strong indicator for next year's profitability, but when the timeframe is increased, more and more 'random' factors come into play.

In relation to Lie's (2001) claim, the positive INDMED variables (in absolute figures) should be smaller than the negative ones, but the contrary is observed in all models. (However, in the Linear model, some signs of this kind of behavior can be seen) The INDMED variables behave in the binary logit models as stated by the profitability persistence theory; current industry relative high profitability is translated into much higher probabilities of being profitable in the future (1-5YRS). Likewise, current low relative profitability increases the odds of having negative profitability in the future. This would support earnings persistence instead of mean reversion of profitability, but on the other hand, the coefficients for INDMED variables are much larger (as absolute figures) for 1YR model than for 3YR and 5YR models. This tells that perhaps some time after the 5 year mark the coefficients might turn around, and the currently above average profitable companies might become below average, even negative profitability companies. This is not due to the nature of the model only, as the proxy for size, LnSales, as well as Age, have even increased coefficients for 3YR and 5YR.

Other variables

The results suggest that in high-techs, larger companies are much more likely to be profitable than smaller ones. An increase of 1 in the logarithm of sales (in millions of USD), e.g. increasing sales from 2 million to 5.5 million, increases the probability of having ROA > 0 21.4% for 1YR, 26.3% for 3YR and 27.4% for 5YR timeframes. Clearly larger companies are more likely to succeed with their business, especially in the mid to long term.

The tests found that the existence of retained earnings has a clear positive effect on future earnings, though it diminishes quite linearly over time. The effect is very similar in the IPO subsample, though the coefficient barely loses its significance for the 5YR model. These results give no support to Demers and Joos (2007) claim that accumulated deficits could be taken as a sign of heavy investment in intangibles and thus promote future profitability, not even on a relatively long 5 year period.

Efficiency of resource use, as proxied by S/TA, is quite important for 1YR profitability, but loses its effect linearly, so that for 5YR model the coefficient is barely positive and not statistically significant. The last variable in the Parsimonious model, Age, is statistically significant in all timeframes, but does not have a very large effect on likeliness of future profitability. The log-odds can be interpreted as follows: every 10 years of operating history increases the likeliness of profitability for 5 percent (1YR) or 7 percent (3-5YR) for mature companies and 14 percent (1YR), 10 percent (3YR) or 13 percent (5YR) for IPOs. The median age of IPOs in the whole sample is 7 years, but 25% of the IPOs have been founded 13 or more years before the IPO. Overall it would seem that the age of a firm brings a moderate amount of 'safety'.

IPO sample

Based on these tests, concurring with Hypothesis 2, risk seems to be more strongly associated with profitability in IPOs. In all (1-5YR) models the pseudo R^2 is clearly higher when the model is run with only IPO companies instead of the whole sample. This is contrary to the argument of e.g. Lui et al. (2007) which states that there should be more uncertainty (less predictability) in new lists.

There are some differences in which variables are meaningful in explaining future profitability in IPOs than in the whole sample. All variables retain their respective signs, but there are differences in which variables are significant. For the 1YR model all variables are significant, but for 3YR and 5YR models S/TA loses its significance. Additionally, for the 5YR model also current profitability and RE > 0 lose their significance, though the latter one is very close to being significant (p=0.053). The insignificance of current profitability is quite surprising even for the IPO group on this relatively long timeframe, but seems to support Jain et al. (2008) findings, where companies are often listed as unprofitable, but later become profitable.

The same effect seems to be prevalent for relative profitability, as for the 5YR model only the POS5, POS10 and POS15 dummies retain their significance. Based on this, only very high profitability compared to the industry has a strong effect on staying profitable after 5 years (1.24 times more likely for POS5X, 1.54 for POS10X and 0.95 for POS15X).

Comprehensive model

Next I will discuss the differences between Parsimonious and Comprehensive models. Contrary to expectation, when more variables are included in the model, both Nagelkerke R^2 and the overall prediction percentage go down. I argue that this is due to the loss of a large amount of observations when adding more complex variables (e.g. 57 326 -> 32 292 for 1YR, loss of 43.67% of observations) and the different nature of these two samples. All of the observations in the Comprehensive model test are included in the Parsimonious model, but the Parsimonious model has many (25 034 for 1YR model) observations exclusively.

The difference in R^2 is smallest in the 5YR models (0.014) compared to 0.037 and 0.022 for 1YR and 3YR models, respectively. These differences are not huge, but taking into account, that more data employed should increase the R^2, not decrease it, I decided to control for the different sample group and run the Parsimonious models again with using the same sample groups as for the Comprehensive models. The results are reassuring; the Comprehensive model beats the Parsimonious model in R^2 in all timeframes, though only by the smallest of margins (0.001 for 1YR, 0.003 for 3YR and 0.001 for 5YR). I tested with Linear regression whether the inclusion of the extra variables in the Comprehensive model and the associated small improvement in the R-Square (after using the same subsample) is statistically significant. The R-Square change value is +0.004 and Sig. F Change 0.000 confirming that the small improvement is indeed a significant one.

The conclusions drawn from the Parsimonious model with the larger sample remain unchanged after this change. My remaining analysis on the difference between Parsimonious and Comprehensive models will focus on the models that use the same sample groups.

It can be concluded that the increased information and model improvement gained from using the Comprehensive models is very small. Fama and French (2005 p.26) experienced similar problems when adding more variables in their profitability model, and pointed towards either measurement errors or collinearity for potential reasons. By looking at the respective coefficients it can be seen that primarily the Parsimonious models express slightly higher coefficients for the common variables in both models, i.e. the majority of the information added by the additional variables is already included in the Parsimonious model variables. Of the additional variables, the most information seems to be included in the TotalAssets change (sign. in 1YR and 3YR, almost sign. in 5YR), STDebt to TDebt (sign. in 1YR and 3YR, almost sign. in 5YR) and EBITDA/TDebt (significant in all models). Interpreting these coefficients is quite straightforward.

A 100% growth in TA during the past year would make a firm 3.3% less likely to be profitable during the next year. Though such an increase seems extreme, for high-techs and especially IPOs it is not unheard of (The top 10% of 42 627 TA changes were larger than 58.90%). This result is in line with Fama and French (2005) findings.

A 10% change in the ratio between short-term debt and total debt would make the firm 0.95% less likely to be profitable during the next year. This has minor economical importance, but it confirms former findings related to profitability and leverage. However, MCAP/TL was not found to be significant in any of the models. This might be due to the fact that the amount of MCAP in comparison to Total Liabilities in this sample is usually large (Sample 1st Quarter 0.88, 2nd 2.05 and 3rd 4.96).

Increasing ‘Debt Coverage’ (EBITDA/TDebt) from e.g. from 1 to 2 would increase the probability of profitability by 1.9% in the 1YR model CA/CL has a slight negative effect on future profitability, though for 5YR it is not statistically significant.

Stock valuation (P/B > 1) seems to have inconclusive results in the binary logit models. For 1YR model companies with P/B > 1 are more likely to be profitable, but for 3YR and 5YR models the log-odds are negative, though not statistically significant. If we held them as reliable in any case, this kind of behavior might be due to overvalued, hyped, companies being able to stay profitable for a short time, but inevitably would ‘show their true colors’. Companies with more prudent valuation would thus end up being less risky in the end. This kind of scenario would seem quite probable for sub-industries such as internet companies or biochemistry firms. However again, these results are not statistically reliable.

Prediction accuracy of models

It is important to see whether the models are effective at estimating future profitability in both ends of the spectrum. Appendix 3 reports the prediction accuracy of the binary models. Both the Parsimonious and Comprehensive models for the whole sample, as well as the IPO models are almost uniformly effective at estimating profitability for those firms that remain or become profitable. However, those companies that will be un-profitable in the future are not identified very well. In the whole sample 5YR models not even half of those cases are estimated properly, which also decreases the total accuracy of the models. The model seems to be more accurate for IPOs in 1YR timeframe, but in 3YR and 5YR models the overall prediction percentage is higher for the whole sample, despite the lower R^2. In these cases the IPO model works better for spotting future negative profitability, but worse when spotting future positive profitability. As the amount of ROA < 0 firms is relatively low, (35% of firms) I decided to try the models with a dependent variable of ROA > Industry Median. In the results of these tests the Nagelkerke R^2 is slightly lower for all timeframe, as well as the overall prediction percentage. However, the accuracy of identifying firms with ‘bad’ profitability is significantly higher.

Next I will discuss the statistical reliability of the tests. The Omnibus tests are significant ($p < 0.05$) for all models. The pseudo R-Squares are relatively high in all models, signaling that the model explains the data quite well. The Hosmer and Lemeshow tests tell us about potential problems with the reliability of the models. In Parsimonious models, only 5YR model gets a Sig. value different from zero (0.001) but it is still not significant (<0.05). However, when the sample is restricted to only IPOs, all the Parsimonious models get a Hosmer and Lemeshow test significantly different from zero, which hints that the large sample size might be the problem showing in the test. For Comprehensive models, only 5YR ‘passes’ the test. The tests with dependent variable ROA > IND. MED. display reassuring results in the Hosmer-Lemeshow tests: the 3YR and 5YR tests are significantly different from zero.

The overall prediction percentage of the model should be larger than the square of the percentage of observed cases (ROA>0 = 1) times 1.25. All of the models fulfill this clause, so the model is better in predicting profitability than a mere guess that all companies are profitable in the future. For example for the Parsimonious 5YR model the overall percentage is 73.8, so the calculation is 0.738 > (0.62*0.62*1.25=0.480).

It can be seen that sample sizes are smaller for the 3YR and 5YR models. This happens for two reasons: firstly, there are less years available for analysis of longer timeframes. Secondly, some firms do not have a consecutive series of 3 or 5 years' profitability figures, which removes them from the analysis. This might potentially lead to a bias in the results, as different companies are included in different models. I control for this by running the regressions for 1YR and 3YR models with the 5YR model sample of 16 936 observations, and the results remain practically unchanged. For the smaller sample size the Nagelkerke R^2 and overall prediction percentages are slightly higher, but the coefficients for explanatory variables are generally lower.

5.4.2 Robustness tests

Ordinal model

Like mentioned earlier, interpreting the coefficients of ordinal models is not a straightforward as a linear model or even a binary logistic model. My results show that if a firm belongs in the least profitable group for year t, it is 95.6% less likely to be in the most profitable group in year t+1 than a company that 'already' belong to that group in year t. For groups 2 and 3 the probabilities are -0.887 and -0.766, respectively. However, when the timeframe is increased, the groups do not seem so 'fixed' anymore. For t+3 years the probabilities are -0.810, -0.629 and -0.524 and for t+5 years -0.673, -0.503 and -0.418 for groups 1, 2 and 3.

The importance of current profitability decreases linearly when moving from 1YR to 5YR both in Parsimonious and Comprehensive models. For IPOs the coefficients are weaker to begin with, and decrease even faster, with none of the coefficients being significant for the 5YR model. For IPOs the probabilities are somewhat weaker in all timeframes, and lose significance for the 5YR model.

In comparison to the results from binary logit models, the models return mainly similar results in terms of variable coefficients. Retained earnings, high sales, asset turnover and age all increase the probability of a firm being in a higher profitability group in the future. Though for these models company age has very little effect. The coefficients react to increments in the timeframe in a similar fashion.

When we look at the tests run only on the IPO sample, we see that the IPO sample models have clearly higher Nagelkerke R^2 for 1YR model, while for 3-5YR the model seems equally effective for the whole sample. Threshold values are clearly higher for IPO models. The strength of current relative profitability (INDMED variables) is clearly higher in IPO models especially for the largest deviance variables. However, current negative deviances from industry are not significant for 3-5YR models. Perhaps this is because IPO companies with negative profitability will either get their current investment projects to create profits in the course of 3-5 years, or go bankrupt/delist from the stock exchange and thus disappear from the data. Seasoned companies are different in this sense, as they have older, already profitable investments in place, as well as new 'prospective' investments, that arguably comprise most of an IPO firm's investment portfolio, especially in the high-tech industry.

RE > 0 and LnSales variables get higher coefficients for IPOs, but S/TA and AGE are not significant in any of the IPO models.

Similarly to the results of the binary logit model, when more variables are included in the model, both Nagelkerke R^2 and the model's accuracy to predict firms in the correct classes decrease. I argue that this is due to the loss of a large amount of observations when adding more complex variables (e.g. for 1YR 57 107 -> 32 168) and the different nature of these two samples. All of the observations in the Comprehensive model test are included in the Parsimonious model, but the Parsimonious model has many (24 393 for 1YR model) observations exclusively.

As in the Binary models, the inclusion of more variables when testing the Comprehensive model changes the sample and makes the two models incomparable. Again, after adjusting for this, the Comprehensive model beats the Parsimonious model in R^2 in all timeframes, though again only slightly (0.002 for 1YR, 0.003 for 3YR and 0.004 for 5YR). See Binary result 4 for explanation about the significance of this change. My remaining analysis on the difference between Parsimonious and Comprehensive models will focus on the models that use the same sample groups.

It can be concluded that the increased information and model improvement gained from using the Comprehensive models is very small. By looking at the respective coefficients it can be seen that primarily the Parsimonious models express slightly higher coefficients for the common variables in both models, i.e. the majority of the information added by the additional variables is already included in the Parsimonious model variables. Of the additional variables, the most information seems to be included in the PtoB_Above1 dummy-variable and STDebt/TDebt ratio, though neither of them are significant in all models.

P/B > 1 variable has the same signs for coefficients for different timeframes as in binary logit models, but surprisingly when in those models the only significant model was 1YR, in ordinal logit only 3YR and 5YR are significant. Market valuation also seems to have a much stronger effect on the relative future profitability (Ordinal model; ROA Groups) than probability of future profitability (Binary model; ROA > 0), and the effect is stronger for longer timeframes in ordinal models, conversely to binary models.

In the Ordinal Models the INDMED variables behave in a similar fashion as in the Binary Models, i.e. momentum is stronger than industry mean reversion of profitability. Again, when the timeframe is increased and/or the sample is restricted to IPOs, the variables on the negative side start losing their significance. Looking at the strength of the coefficients, in Parsimonious 1YR model the POS10X coefficient is about 2 times higher than the POS2X coefficient, which makes firms in that relative profitability class twice as likely to be in higher group ceteris paribus.

The Ordinal models have some issues regarding their statistical reliability. The model fit statistic is in order in all of the models, the sig. reported is 0.000. The pseudo R-Squares in all models tell that the model explains a large and significant portion of the variation in the data. The Goodness-of-Fit statistics for Ordinal models should be above 0.05 to show that the model fits the data well. For Pearson and Deviance both of these requirements are not met simultaneously in any of the models. Both the Parsimonious and Comprehensive models all receive the value 0.000 for Pearson (<0.05) and 1.000 for Deviance (>0.05). However, neither of these statistics work well with large datasets such as mine, and also with data that includes lots of missing cells. All in all, the 'breach' in these requirements should not be considered a model breaking issue, but they raise some concern about the reliability of the results. Similarly with the test of parallel lines, the models exhibit statistical problems. The null hypothesis of not meeting the proportional odds assumption is not rejected, which again hints of possibly unreliable results. However, similarly as with Goodness-of-Fit tests, the test of parallel lines is very sensitive to changes in large datasets, and easily gets rejected. A method for controlling for the rejection of proportional odds assumption is running separate binary logit models for the groups used in Ordinal regression, and see if a coefficient changes significantly in the separate models. This is not reported, but the coefficient signs are stable in other variables but the INDMEDs.

Multinomial model

Like explained above, Ordinal regression assumes same coefficients for all classes of the dependent variable. However, different variables are important for explaining future profitability in different ends of the spectrum. The regression output for multinomial regression is interpreted in a different way than for ordinal regression, but most of the results are similar in these two models, when properly analyzed. As the idea of testing the model with this kind of regression was primarily a supplementary sort of analysis to ascertain the statistical reliability of the earlier models, I will not go into too much detail about the coefficients. Besides the reliability of the model, I will focus on surprising details and changes in signs between different timeframes. On a side note, the Multinomial models had to be run without country dummies, because including all of them made the model too heavy for SPSS to run it. However, this should not be a problem, since country dummies are included in all the main analyses.

The likelihood tests tell us that all of the explanatory variables in the Parsimonious model are statistically significantly associated with the independent variable in all timeframes. However, in Comprehensive models Profitmargin loses its significance, which can be explained by the fact that the information included in the variable (EBIT and Sales) is already included in the other variables in the model. In fact, Profitmargin was not found significant in any other earlier model either, which increases the apparent reliability of my earlier results. In the IPO sample some variables are not significant in the Parsimonious model. S/TA in 1YR model, S/TA and AGE in 3YR model and AGE in 5YR model are insignificant, so their meaning in the earlier models can be questioned. However, neither of those variables was significant in any IPO ordinal models, and S/TA was also insignificant in 3YR and 5YR binary models.

When comparing the Parsimonious models' regression output groups 1, 2 and 3, it can be seen that for Groups 1 and 2, the signs for statistically significant variables are identical, with the exception of 5YR model's Group 1, where S/TA gets a positive and significant sign. I cannot think of a reason that would make companies with smaller asset turnovers more likely to be very unprofitable than very profitable after 5 years, other than sheer coincidence related to the data.

Like suspected when discussing the Ordinal models, the biggest problems with continuity lay with the INDMED variables. In Group 1 quite consistently positive deviances from industry median mean that the firm is less likely to belong in the bottom group than the top group, and vice versa for negative deviations, though most of those variables are insignificant. However, Groups 2 and 3 are much more complicated in this sense. They get negative coefficients in all of the INDMEDs, only larger in the positive ones. The tests seem to suggest that if a company is very far from industry median, on either side of it, it is more likely to be only in the middle of relative profitability (>25% but <75% of sample) in any timeframe we focus on. This means that the firms in the top25% future profitability group would emerge from the 'average' group of firms. We should keep in mind that binary and ordinal models showed very simplistically that better profitability than industry would translate as high future profitability, and likewise downward deviances would show as low future profitability.

The model fit sig. is 0.000 in all models, so the model seems to fit the data and reject the null hypothesis that there is no connection between the independent and dependent variables. None of the standard deviances of the coefficients are above 2, so there should not be any serious multicollinearity. For the Comprehensive models in Group 1 the standard error of year dummy 1990 exceeds 2, which is most likely due to a very small number of cases, of which none or very few belong in Group 1.

The Goodness-of-Fit statistics for Multinomial models give mixed signals. For Parsimonious 1YR and 3YR models they are identical to the Ordinal models, i.e. the same potential problems persist. Parsimonious 5YR, Comprehensive 3YR and Comprehensive 5YR models have both statistics on acceptable levels. Comprehensive 1YR has Pearson 0.021, which is larger than zero, but not statistically significantly (<0.05). These results can still be seen as increasing our confidence in the statistical reliability of the earlier models. The Pseudo R-Squares remain on a satisfactory high level.

Insignificant variables

Some variables and their effect on future profitability are left unreported in this study. They were observed to have no statistically significant effect on profitability in this sample, i.e. they were not adding any power to the models or faced multicollinearity issues. These variables include: Earnings growth/volatility, Depreciation/Accruals, Operating leverage, ROA change from year t-1, CFO/NI, RD/Sales and Dividend payment status.

6. Conclusions

The main goal of this study was to uncover the relationship between fundamental risk and future profitability in high-tech firms. Earlier literature gave several hints of the existence of such an association. However, the direction of the association could not be predicted reliably. Would riskiness lead to higher future profitability in this sample, like finance theory suggests, or would it lead to increased financial distress and thus lower future profitability?

Special focus in the empirical part was put to studying simply which factors make firms become profitable (ROA > 0) in the future. Sensitivity analyses were also made to extract more information about which characteristics lead a high-tech company to be among the very worst or best future performers. Additionally, it was tested whether the uncertain nature of IPO companies leads to fundamental risk proxies being better or worse at explaining their future profitability.

The tests were done on an international sample of 14 749 publicly listed firms defined as high-techs by their industry code. The amount of observations used in the regressions ranged from 32 168 for the 1YR models to 16 850 for the 5YR models.

The results of the tests are not completely expected. With binary logistic regressions it was found that current profitability, relative profitability against industry, firm size and the existence of retained earnings are all positively and significantly related to the probability of the firm being profitable in the future. To a lesser extent, effective resource use, firm age, higher average maturity of debt and higher debt coverage were found to be positively associated with future profitability. All these results support the claim that risk is associated with lower future profitability. However, it was also found that growth was negatively associated with future profitability. This finding is in line with Fama and French (2005) and Fairfield et al. (2003), but it is still not completely clear how this should be interpreted. One could suspect that fast growth is risky and leads to decreased future profitability when measured with ROA. Often companies are unable to keep costs down as they aggressively increase their sales.

In the complementary tests the robustness of the main tests was further increased. The ordinal regressions found almost identical factors to be associated with future profitability. However, growth was only found to be significant for 3YR and 5YR models, and the sign was positive. This could be explained by the different profitability measure, as growth is arguably needed for a firm to achieve the highest profitability class in its industry. For the longer timeframes also market valuation of stock was found to be significantly positively associated with future profitability.

Multinomial logit models were run to confirm the statistical reliability of the ordinal models. It was found out that most of the potential statistical problems in those model were presumably due to peculiar behavior of the industry median deviance variables. It can be seen that generally the least profitable firms are likely to have been in the least profitable group also in the past. The group that is among the most profitable in the future on the other hand mainly come from the group of average profitability. This is opposite of what McGahan and Porter (2003) found with no industry focus; that low profitability is persisting, but high profitability is not. This might be because high-tech industry is very competitive, and sustaining a commanding market position is very tedious.

The main tests together with the robustness tests give strong support to Hypothesis 1; the existence of an association between fundamental risk and future profitability. Furthermore, based on the individual coefficients of the risk variables, the relationship was almost uniformly found to be negative, i.e. riskier high-tech companies are expected to be less profitable in the future. Thus it can be said that in the high-tech industry risk does not realize as higher future profitability like finance theory would imply, but the opposite. Qian and Li (2003) reason that this might be due to the inability of small, risky high-techs to endure market turbulence that is evident in this industry. Perhaps also the high R&D expenses and ‘light’ balance sheets these firms often have are to blame for the different risk behavior.

Additionally it was found that the explanatory power of the models is persistently higher for IPO firms, which means that the association between fundamental risk and future profitability is stronger in IPOs than in mature firms, like stated in Hypothesis 2. Otherwise IPOs behave almost uniformly with mature companies in this matter. However, the additional explanatory power when using a more complete set of financial statement figures is statistically significant, but almost inexistent, which means that support for Hypothesis 3 cannot be given. The results of this study are unique, as such analysis has not been done before on a large, international high-tech sample. More light on the important question of determinants of profitability has been shed.

The various robustness tests increase the reliability of the results obtained in the empirical study. However, there are several limitations to this study. First, the test sample consists of only high-tech companies, so the results cannot directly be generalized in other industries. Secondly, the models used are not compared with the same sample to their traditional counterparts in this study. Additionally, the selection of the variables used in the estimation model was done by combining results from earlier studies, so the method is not per se connected to a single theory, though each variable has theoretical backing.

A potential caveat to the results obtained is data mining issues. As a complete selection of data is available for only a small fraction of the 14 749 firms in the sample, it is possible that this leads to some kind of bias in the results. Implicitly I suspect that the companies that have the largest percentage of data available are on average larger and more profitable companies than those that have more missing data. However, I control for this by running the tests for a one year period for the year that has the largest amount of available data; 2006. There are no large differences in the results, though the much smaller sample size causes some of the variables to become insignificant. This finding confirms the inexistence of autocorrelation in the results, which is reassuring for the reliability of the results.

During the course of this study I saw several possible ways of expanding this study. The models developed could be used in out-of-sample tests to see if they can forecast profitability in the same industry or even other industries. More complete data could be collected from multiple sources, to make the analysis more reliable and complete. Also, better information about delistings would help in reducing the possibility of biases. IPOs could be focused on more thoroughly, e.g. it could be compared how the same company behaves after the IPO in terms of risk and profitability. A wider range of variables, including stock market information, could be used in estimating future profitability. More sophisticated analysis is required to ascertain how risk influences profitability.

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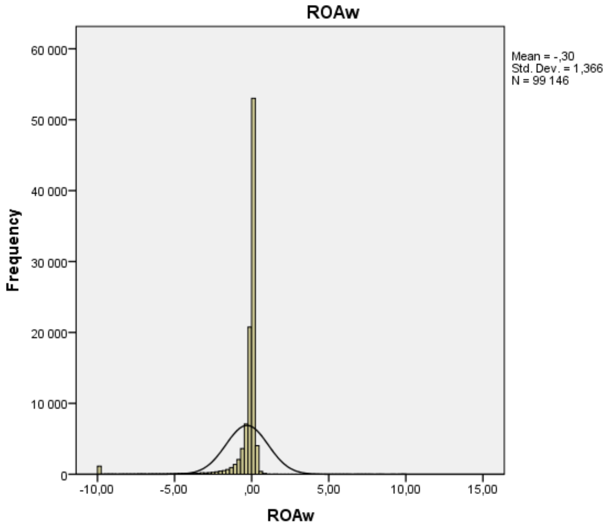
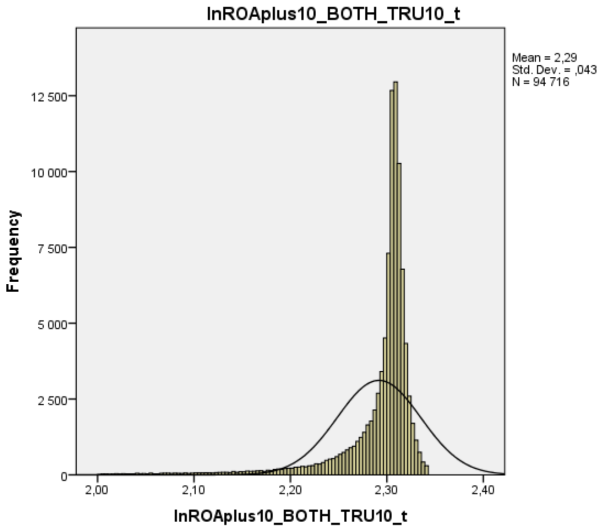
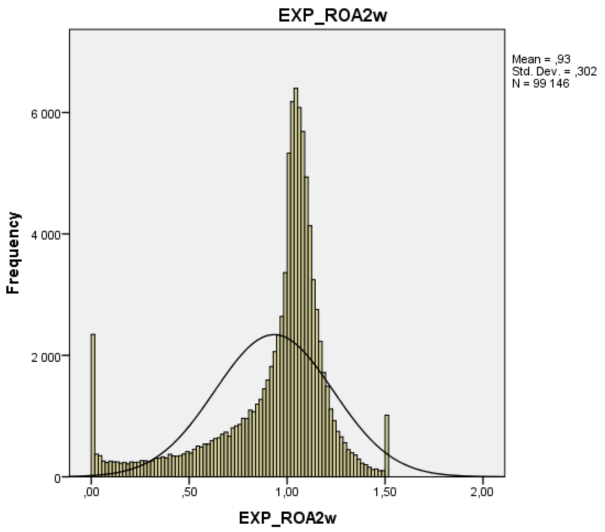
Appendix 1


ROAw
Mean = -,30
Std. Dev. = 1,366
N = 99 146
Frequency
60 000
50 000
40 000
30 000
20 000
10 000
0
-10,00
-5,00
,00
5,00
10,00
15,00
ROAw


lnROAplus10_BOTH_TRU10_t
Mean = 2,29
Std. Dev. = ,043
N = 94 716
Frequency
12 500
10 000
7 500
5 000
2 500
0
2,00
2,10
2,20
2,30
2,40
lnROAplus10_BOTH_TRU10_t


EXP_ROA2w
Mean = ,93
Std. Dev. = ,302
N = 99 146
Frequency
6 000
4 000
2 000
0
,00
,50
1,00
1,50
2,00
EXP_ROA2w

Appendix 2

Table 15: Linear OLS model example

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,671[a]	.451	.450	.02724	2.059

b. Dependent Variable: lnROAplus10_1YRSforward_t

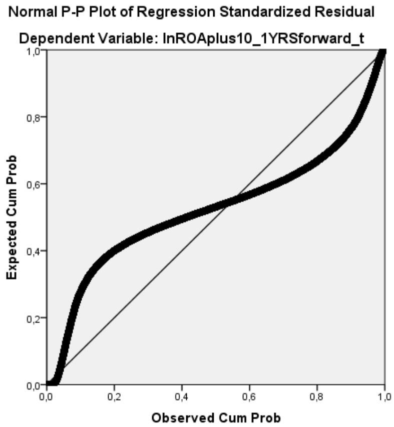
ANOVA[a]

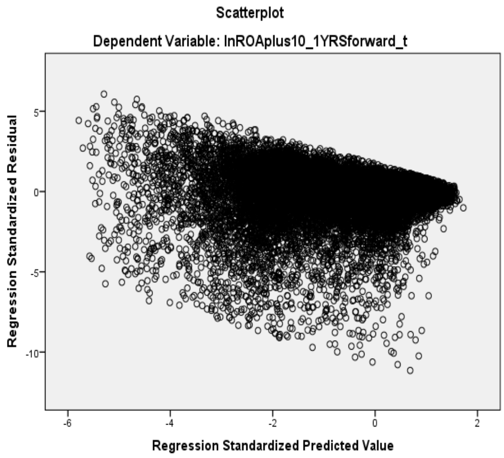
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.681	113	.307	413.676	,000[b]
	Residual	42.241	56935	.001		
	Total	76.922	57048			

a. Dependent Variable: lnROAplus10_1YRSforward_t

Coefficients[a]

Model		Unstandardized Coefficients		Std. Coeff.			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.486	.013		112.388	0.000					
	lnROAplus10_BOTH_TRU10_t	.346	.006	.341	60.214	0.000	.623	.245	.187	.300	3.331
	RetEarnings0	.003	.000	.039	9.975	0.000	.371	.042	.031	.633	1.580
	LnSales	.002	.000	.145	37.067	0.000	.437	.154	.115	.627	1.594
	StoTA_w	.002	.000	.043	13.126	0.000	.113	.055	.041	.898	1.114
	ROA_IND2MED_POS2X	.003	.000	.039	10.229	0.000	.212	.043	.032	.678	1.476
	ROA_IND2MED_POS5X	.007	.000	.060	16.246	0.000	.197	.068	.050	.708	1.412
	ROA_IND2MED_POS10X	.008	.001	.037	11.083	0.000	.104	.046	.034	.850	1.176
	ROA_IND2MED_POS15X	.007	.001	.023	6.884	0.000	.075	.029	.021	.834	1.199
	ROA_IND2MED_NEG2X	-.002	.000	-.015	-4.437	0.000	-.026	-.019	-.014	.812	1.231
	ROA_IND2MED_NEG5X	-.008	.001	-.053	-14.856	0.000	-.110	-.062	-.046	.756	1.323
	ROA_IND2MED_NEG10X	-.010	.001	-.056	-15.692	0.000	-.136	-.066	-.049	.765	1.307
	ROA_IND2MED_NEG15X	-.020	.001	-.173	-29.428	0.000	-.537	-.122	-.091	.280	3.571


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: lnROAplus10_1YRSforward_t
Expected Cum Prob
Observed Cum Prob
0,0
0,2
0,4
0,6
0,8
1,0


Scatterplot
Dependent Variable: lnROAplus10_1YRSforward_t
Regression Standardized Residual
Regression Standardized Predicted Value
5
0
-5
-10
-6
-4
-2
0
2

Appendix 3

Table 16: Prediction accuracy of Binary models

Comprehensive 1YR		**Parsimonious 1YR**		**Comprehensive 3YR**		**Parsimonious 3YR**		**Comprehensive 5YR**		**Parsimonious 5YR**		**IPO 1YR**		**IPO 3YR**		**IPO 5YR**	
Percentage correct		Percentage correct		Percentage correct		Percentage correct		Percentage correct		Percentage correct		Percentage correct		Percentage correct		Percentage correct	
0	68.8	0	68.8	0	53.0	0	53.2	0	48.4	0	48.4	0	77.7	0	64.3	0	59.5
1	88.1	1	88.1	1	88.4	1	88.1	1	89.0	1	88.9	1	89.5	1	82.9	1	81.7
Total	**81.1**	Total	**81.1**	Total	**76.0**	Total	**75.8**	Total	**75.2**	Total	**75.1**	Total	**84.5**	Total	**74.6**	Total	**72.4**

Percentage correct: first row percentage when ROA<0, second row when ROA>0, third row total percentage correct. Parsimonious and Comprehensive models reported when same sample is used.

Appendix 4

Table 17: Multinomial regression models

	Model	Parsimonious 1YR		Parsimonious 3YR		Parsimonious 5YR	
Threshold	**Variable**	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
1	Intercept	0.520	0.000	0.951	0.000	0.569	0.000
	RE > 0 DUM	-0.803	0.000	-0.593	0.000	-0.525	0.000
	LnSales	-0.300	0.000	-0.338	0.000	-0.342	0.000
	S/TA_w	-0.165	0.000	-0.019	0.358	0.056	0.025
	AGE	-0.010	0.000	-0.012	0.000	-0.012	0.000
	ROA_INDMED_POS2X	-1.450	0.000	-0.867	0.000	-0.538	0.000
	ROA_INDMED_POS5X	-1.736	0.000	-1.107	0.000	-0.858	0.000
	ROA_INDMED_POS10X	-1.920	0.000	-1.243	0.000	-0.969	0.000
	ROA_INDMED_POS15X	-1.126	0.000	-0.857	0.000	-0.846	0.000
	ROA_INDMED_NEG2X	0.314	0.003	0.055	0.576	0.133	0.242
	ROA_INDMED_NEG5X	0.384	0.002	0.117	0.286	0.219	0.065
	ROA_INDMED_NEG10X	0.331	0.028	-0.001	0.992	0.117	0.409
	ROA_INDMED_NEG15X	0.159	0.242	-0.041	0.741	0.213	0.119
	[ROA_GROUP=1]	2.795	0.000	1.696	0.000	1.114	0.000
	[ROA_GROUP=2]	2.129	0.000	1.117	0.000	0.823	0.000
	[ROA_GROUP=3]	1.164	0.000	0.715	0.000	0.539	0.000
	[ROA_GROUP=4]						
2	Intercept	0.110	0.264	0.523	0.000	0.275	0.024
	RE > 0 DUM	-0.333	0.000	-0.137	0.000	-0.104	0.022
	LnSales	-0.092	0.000	-0.114	0.000	-0.118	0.000
	S/TA_w	-0.154	0.000	-0.101	0.000	-0.066	0.012
	AGE	-0.002	0.020	-0.005	0.000	-0.006	0.000
	ROA_INDMED_POS2X	-1.823	0.000	-1.087	0.000	-0.674	0.000
	ROA_INDMED_POS5X	-2.458	0.000	-1.522	0.000	-1.076	0.000
	ROA_INDMED_POS10X	-2.628	0.000	-1.847	0.000	-1.358	0.000
	ROA_INDMED_POS15X	-2.896	0.000	-1.851	0.000	-1.395	0.000
	ROA_INDMED_NEG2X	-0.118	0.226	-0.167	0.072	-0.163	0.122
	ROA_INDMED_NEG5X	-0.482	0.000	-0.467	0.000	-0.417	0.000
	ROA_INDMED_NEG10X	-0.768	0.000	-0.717	0.000	-0.505	0.000
	ROA_INDMED_NEG15X	-1.751	0.000	-1.225	0.000	-0.856	0.000
	[ROA_GROUP=1]	2.250	0.000	1.220	0.000	0.831	0.000
	[ROA_GROUP=2]	2.168	0.000	1.042	0.000	0.780	0.000
	[ROA_GROUP=3]	1.273	0.000	0.693	0.000	0.480	0.000
	[ROA_GROUP=4]						
3	Intercept	0.449	0.000	0.319	0.000	0.156	0.109
	RE > 0 DUM	0.018	0.561	0.073	0.028	0.079	0.036
	LnSales	0.018	0.016	0.020	0.010	0.024	0.006
	S/TA_w	-0.066	0.000	-0.017	0.347	-0.009	0.666
	AGE	0.001	0.150	0.001	0.426	0.000	0.704
	ROA_INDMED_POS2X	-1.146	0.000	-0.753	0.000	-0.433	0.000
	ROA_INDMED_POS5X	-1.998	0.000	-1.283	0.000	-0.836	0.000
	ROA_INDMED_POS10X	-2.423	0.000	-1.719	0.000	-1.242	0.000
	ROA_INDMED_POS15X	-3.041	0.000	-2.050	0.000	-1.518	0.000
	ROA_INDMED_NEG2X	-0.385	0.000	-0.225	0.012	-0.310	0.002
	ROA_INDMED_NEG5X	-0.867	0.000	-0.695	0.000	-0.522	0.000
	ROA_INDMED_NEG10X	-1.176	0.000	-0.919	0.000	-0.678	0.000
	ROA_INDMED_NEG15X	-2.086	0.000	-1.391	0.000	-1.124	0.000
	[ROA_GROUP=1]	1.222	0.000	0.746	0.000	0.698	0.000
	[ROA_GROUP=2]	1.227	0.000	0.616	0.000	0.591	0.000
	[ROA_GROUP=3]	1.482	0.000	0.821	0.000	0.655	0.000
	[ROA_GROUP=4]						
	Nagelkerke R^2	0.626		0.429		0.352	
	N	57107		42264		29436	

Threshold means the crossing point between Groups 1 and 2, 2 and 3 and 3 and 4. The coefficients are reported in those points.