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COMPARISON OF R&D INTENSIVE INVESTMENT STRATEGIES ON THE U.S. STOCK MARKETS

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Abstract

Chan, Lakonishok and Sougiannis (2001) suggest an R&D intensive investment strategy, which results in excess return with high R&D intensive portfolios. We show how this investment strategy can be improved by taking into account the different industries and the competitive strategy. For this purpose we develop a simple proxy for Porter’s product differentiation and cost leadership strategies from DuPont identity components. Our strategy proxy seems to provide a good screen for stocks with negative excess returns. However, the improved excess returns are partly increased by loading unexplained risk.

We partly replicate Chan et al. (2001) study for the period 1975-2011 with comparable results. We find the highest R&D intensity portfolios have excess returns after controlling for common risk factors. These stocks seem to be past losing stocks. In contrast to the reference study, we found slightly higher excess returns. The difference is explained by the different time period and lack of CRSP delisting return data in our study. We find support for our first (H1) hypothesis.

H1: R&D intensity (measured by R&D expenses to market value of equity) has explanatory power over stock returns.

To develop the investment strategy we explore the excess returns separately in ten different industries classified by SIC codes. After controlling for common risk factors, we show that R&D intensive portfolios’ excess returns are the phenomenon only in certain industries. These industries are hitec, healthcare and manufacturing. However, results for manufacturing excess returns were only slightly positive and lasted only for a year. We find support for our second (H2) hypothesis.

H2: R&D intensity (measured by R&D expenses to market value of equity) has explanatory power over stock returns only among the high R&D intensity industries.
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1 INTRODUCTION

1.1 Background

R&D investments fall into the category of intangible investments. From the investor’s point of view, intangible investments are problematic because they introduce valuation issues (Daniel & Titman 2006). Broad academic literature referenced in this study shows the evidence for a positive stock return relation to R&D intensity. However, there exists no consensus about the reason for this relation. One group of studies is in favor of the mispricing explanation (Eberhart, Siddique & Maxwell 2004; Lev, Sarath & Sougiannis 2005; Lev, Nissim & Thomas 2007). Another set of studies justify the R&D and stock return relation to be risk compensation for R&D investments (Kothari, Laguerre, Leone 2002; Chambers, Jennings & Thompson 2002; Ho, Xu & Yap 2004).

Since R&D investments are high risk, many of them fail. Lev (2001) argues that only a few product or process innovations will benefit companies. When most of the reference articles testify that R&D contributes positively to stock returns, some opposite results also exist (Chan, Lin & Wang 2010; Saad & Zantout 2012). Poor performance of the companies is explained by the overinvestment hypothesis introduced by Jensen (1993, 2005).

We are not seeking an explanation for the valuation issue by searching for the missing risk factor. Instead, we further develop the investment strategy introduced by Chan, Lakonishok & Sougiannis (2001), which concentrates on the high return potential R&D intensive stocks. In this study we discuss the risks and accounting-related issues, which are connected to R&D intensive companies. The purpose is to introduce different valuation problems, which relate on to these companies. Investors should be aware of these issues when considering investments in R&D intensive stocks. We further approach the R&D intensive companies from Porter’s competitive strategy point of view with the idea of enhancing the R&D intensive investment strategy returns.
Company strategy plays a major role in a company’s success. Companies which are able to follow the right strategy in different economic states are likely to outperform others. The importance of the strategy selection is emphasized when the company needs to maintain a high level of risky investments such as R&D. Sacrifices on R&D may pay out for investors as higher stock returns, which depends on the success of the R&D projects.

R&D investments that improve company’s value require company to create the right products at the right time not forgetting the costs. An R&D project may succeed, but market timing of the new product can fail and make the investment unprofitable. In the end, a company can burn all the R&D money with no cash flow generation. Porter (1985, 181-182) gives a plausible explanation. He argues that R&D needs to be connected to the firm’s value chain. Putting it another way, the firm’s R&D needs to be part of the competitive advantage strategy to succeed.

In the U.S. accounting rules require to expense R&D costs (SFAS) No. 2 (FASB 1974). R&D has therefore an audited and observable figure in financial statements. This figure offers a possibility to study the R&D investments. However, this expensing rule might mislead investors because R&D benefits usually materialize after a long time. The R&D investments can therefore be seen as either out of balance sheet investments or hidden reserves (Lev et al. 2007). This is information which investors might be unable to recognize if they fixate on earnings. Sloan (1996) shows how investors fixate on earnings which will lead stocks to be misvalued.

R&D intensity and its importance differ across the industries (Lev & Sougiannis 1996, Amir, Guan, Livne 2007). For example, pharmaceutical industry invests a high portion of income in R&D, while in wholesale bets on the R&D are small. Industries are in different states of maturity which may have an effect on the R&D investment profitability. In some industries a high level of R&D capital co-exists with high competition. High competition drives down the excess profits and has eventually an effect on the stock returns. Therefore we study different industries separately to find the industries where R&D is the most value relevant for investors.
1.2 Specific Risks with R&D

Traditional risk factors most likely fail to take into account all the risks which are included in R&D investments. Academic studies have been unable to point out the missing risk factor. R&D investments clearly affect the business risk, but also have an effect on the information risk (Ho et al. 2004, Aboody & Lev 2000). A higher business risk requires investors to demand for higher returns from R&D intensive firms. The information risk leads to a similar return requirement, but can be mitigated by standard setters with more precise disclosure requirements. However, U.S. accounting rules do not require companies to disclose precise information related to ongoing R&D projects.

With high R&D intensity investors face high information uncertainty of future cash flows. Many of the highest intensive companies are opportunistic in nature. These companies tend to be small start-ups with very low or no cash flow generation. Many of these start-ups fail, but when they succeed they can provide astronomical returns. However, the information risk concerning the start-up companies is severe because they need to protect their new products from potential rivals.

Small start-up companies usually have just one R&D project. With one R&D project firm faces higher risk than with multiple projects. Larger companies can diversify this risk by running several R&D projects at the same time. They may also enjoy economies of scale due to spillover effects. Especially this applies to the companies, which operate in R&D intensive industries (Ciftci & Cready 2011). Scale effects have been shown to reduce the R&D related risks (Hand 2002).

Studies which testify to the positive relation between R&D and future market performance cannot agree on the reason for the relation. Some studies prefer the market compensation for the risk explanation, while other studies are in favor of the mispricing R&D relation. Therefore numerous studies address the R&D and risk relation (Lev & Zarowin 1998; Chan et al. 2001; Boone & Raman 2001; Chambers et al. 2002; Kothari et al. 2002; Shi 2003; Ho et al. 2004; Amir et al. 2007; Li 2011).
Lev & Zarowin (1998) conduct study across firms and industries between the stock market’s valuation of R&D expenditures and the risks included in R&D. They show that the market’s valuation of R&D varies in cross-section reflecting the fundamental benefits and risks from R&D. Chan et al. (2001) study stock return volatility on R&D, controlling for firm size, age and industry effects. They show R&D intensity to be positively correlated with return volatility, supporting the risk-based explanation for found risk factor controlled excess returns.

Boone & Raman (2001) show that off-balance sheet R&D assets are associated with lower market liquidity due to information asymmetries concerning R&D investments. Information asymmetry can lead to higher bid-ask spreads, which implies higher cost of capital. Due to information asymmetry, investors who are able to obtain private information can impose liquidity costs on other market participants due to adverse selection. Investors who are holding these less liquid stocks need to be then compensated with higher stock returns.

Boone & Raman (2001) use intraday stock transaction data to measure the average adverse selection component of the bid-ask spread and the quoted depth. They show that the adverse selection component of the spread is higher for R&D intensive firms than non-R&D firms. Further, the adverse selection component share is associated with R&D capital and the change in the component is associated with the change in the R&D capital. These results support the finding of Aboody & Lev (2000), who show that R&D leads to information asymmetry among insiders and other stock holders.

Information asymmetries created by R&D investments have implications for the company’s capital structure. Bah & Dumontier (2001) study the financial choices of R&D intensive firms. According to them, R&D intensive firms use more equity and less debt, reflecting the severe information asymmetries. Due to information asymmetries, R&D intensive companies’ debt markets are stricter with a higher margin compared to non-R&D companies.
Al-Horani, Pope & Stark (2003) use Fama and French three-factor model regressions adding R&D as a risk factor. They find that stock returns relate positively to R&D and the relation helps to explain cross-sectional variation in UK stock returns. They show that the addition of R&D activity can significantly enhance the explanatory power of the three-factor model. They further show that the estimated risk premium based on the modified three-factor model is different from the estimated risk premium with Fama-French three-factor model. According to Al-Horani et al. (2003), in industries where few firms undertake R&D activities the risk premium tends to be overestimated.

Ho et al. (2004) explore the relation of R&D to systematic risk. Similar to Chan et al. (2001), they find R&D intensity to be positively related to stock return volatility. They show that the stocks of R&D intensive firms have greater systematic risk. According to Ho et al. (2004), the higher systematic risk arises from a higher business risk measured by volatility of sales. The other affecting factor, according to them, is the greater operating risk of the R&D intensive companies. Similar to Bah & Dumontier (2001) they note that high R&D intensive firms are financially less leveraged.

Shi (2003) takes the creditor’s view to the R&D risks with results supporting Bah & Dumontier (2001). He studies bond ratings and bond risk premiums on R&D. He shows that R&D investments are positively associated with bond risk premium and bond default risk. According to Shi the correlation varies strongly between industries. He states that R&D intensity explains 80% of the bond risk premium and default risks.

Eberhart et al. (2008) show results opposite to Shi. According to Eberhart et al. (2008), R&D intensity correlates with lower risk premiums and lower default risks.

Also Li (2011) studies the R&D effect on the firm’s capital structure. Inability to get funding may lead a company to face tightening financial conditions. Companies engaged in R&D facing financial constraints are more likely to cancel their R&D projects. According to Li (2011), this is the reason why, constrained firm’s risk increases with R&D intensity. Li (2011) further states that R&D predicts returns only among financially constrained firms. She argues that financial constraints drive the potential positive R&D intensity stock return relation supporting the risk based explanation.

Accounting literature shows that company financial performance measures correlate positively with high R&D intensity. However, high R&D intensity can lead to higher volatility of these performance measures, for example profitability. The reasoning is similar to Chan et al. (2001) excess stock returns contribution to risk explanation. However, the less discussed problem within these studies is the causality. Is R&D the origin of profitability or does profitability make it possible to invest in R&D? (Kothari et al. 2002; Chambers et al. 2002; Amir et al. 2007).

Kothari et al. (2002) study earnings variability in different type of investments and other factors which affect earnings volatility like firm size and leverage. They show that tangible investment leads to lower earnings variability than intangible investments. R&D investment results in more volatile earnings than PP&E. Amir et al. (2007) conduct a similar study for a slightly different time period. Their results support the findings of Kothari et al. (2002). Amir et al. (2007) also study the relation in different time periods across industries. They argue that R&D investments only contribute to earnings variability in industries which R&D is relatively more intensive than physical capital.

Chambers et al. (2002) study the reasons behind the R&D intensive firm excess returns phenomenon. They address the question whether these returns are due to
mispricing or compensation for the extra risk. They conclude that the positive correlation between R&D intensiveness and excess returns is more likely due to inadequate risk control of the traditional models. However, they cannot rule out the mispricing explanation for the changes in the R&D intensity level. Lev, Nissim & Thomas (2007) state just the opposite. According to them, mispricing is more related to the R&D intensity level than the changes in that level. However, they suggest that after two years, the abnormal returns are compensation for the risks rather than mispricing.

1.3 Accounting Treatment of R&D Expenditures

As noted earlier chapter, the accounting treatment of R&D expenses has an effect on the information risk that R&D investments impose. This gives a good reason to discuss the intangibles, their accounting treatment and the related problems.

Intangible investments such as R&D differ from tangible investments on many aspects. These aspects have been difficult for investors and for standard setters. In the U.S. accounting rules requires to expense R&D costs (FASB 1974). From the accounting point of view R&D fails to meet the controllability and identifiably criteria. The main justification for the expensing treatment is the prudence principle, which restricts companies to overstate their income. Capitalizing the high-risk R&D investments might lead companies to show too high earnings.

Intangible investments have some characteristics which make them to different from tangible investments. Intangible investments are unique. No R&D projects or their output products are the same. The uniqueness makes R&D outputs hard to value and to compare to tangible investments. Tangible investments are usually investments on physical capital such as PP&E, which has limited technical or economical lifetime. These investments can be capitalized and amortized over the period during which they contribute to the company earnings. Tangible investments can also be valued on the markets and thus they have a collateral value. These differences give some
explanation why valuation issues rise with the intangibles. (Kothari, Laguerre & Leone 2002.)

In the stock market, accounting practices might have an effect on stock prices when they hide some valuable information. Stock analysts interpret this information while seeking for private information. These analysts are often seen as sophisticated investors because they put more emphasis on the data such as economic forecasts, interest rates, political trends and the accounting data. They are probably also better trained to analyze this data than average investor. Analysts also interview the management of the companies they follow. These interviews give valuable non-disclosed information to the analysts. Despite their sophistication and high interest in R&D stocks, analysts might not be able to dig out private information about R&D intensive stocks.

Barth, Kasznik & McNichols (2001) show that analyst interest is higher for high R&D and advertising intensity firms. According to them, analyst interest in companies with a high level of intangibles reflects their private benefits from analyzing these companies. These private benefits fall from brokerage fees and consulting payments that analysts can collect.

Multiple studies show analysts’ forecast errors to be associated with the level of intangibles (Barron et al. 2002, Amir, Lev & Sougiannis 2003, Gu & Wang 2005). Barron et al. (2002) show that forecast errors are larger as the level of intangible assets increases. Amir, Lev & Sougiannis (2003) and Gu & Wang (2005) find support to Barron et al. (2002) by showing analysts’ forecast errors to be associated with the R&D intensity. These studies show that analysts cannot complement the unavailable information about R&D on their analysis. Analysts seem to fixate on earnings in the case of R&D investments.

The fixation on earnings is explained by functional fixation hypothesis presented by Sloan (1996). Functional fixation hypothesis states that investors are unsophisticated and therefore fail to adjust shown earnings to real earnings. According to Sloan
(1996), investors are too much focused on income statement earnings and fail to fully adjust these earnings to balance sheet accruals and cash flow components. His research from the years 1973-1991 shows that stock prices act as if investors fixate on earnings.

The functional fixation hypothesis, contradicts the efficient market hypothesis presented by Fama (1970). Fama suggests that stock prices follow random walk and are unpredictable. The efficient market hypothesis requires the market to be informationally efficient. Its strongest form suggests that all market participants share the same market information at the same time. If the efficient market hypothesis holds, one cannot consistently earn returns which exceed the average market return. This requires stock prices to reflect all the available information. Stock prices are determined on the stock markets where investors analyze the information available. If the investors fail to analyze firms consistently, it leads to stock mispricing.

The U.S. GAAP requirement for immediate expensing of R&D costs connects to the functional fixation hypothesis by creating out of balance sheet investments or hidden reserves. According to the functional fixation hypothesis, investors leave these investments without notice. As Sloan (1996) shows investors may disregard these items. Moreover, uncertain R&D projects with limited public information challenge investors to do careful information analysis for the right stock valuation. If investors place too much emphasis in their analysis on earnings, the disclosed R&D expenses might mislead investors because of their immediate impact on earnings.

Because of investor fixation, depressed earnings may lead to depressed stock prices if the information incorporates slowly into the stock prices. A behavioral view for the above phenomenon is mispricing, which leads to excess returns when the benefits from the R&D materialize. Underreaction to market information can be explained by slow information adaptation on the markets (Hong & Stein 1999).
Barberis, Schleifer & Vishny (1998) offer an explanation which is based on the framework of conservatism. According to Barberis et al. (1998), conservative investors cause the underreaction in the short run, because they are reluctant to accept new information. However, in the case of R&D there might be more to explain. The benefits from R&D are shown to be long-lived and found excess returns have been shown to last up to five to ten years (Chan et al. 2001; Chambers et al. 2002).

Daniel, Hirshleifer & Subrahmanyam (1998) explain the stock mispricing with overconfidence and biased self-attribution. Overconfident investors overestimate their abilities and trust the precision of their own estimates, putting too little weight on market information. Investors, with biased self-attribution regard their own view as the right estimate and underreact to market information. With a high level of R&D capital the investors have more room for interpretations, which increases the mispricing risk.

Aboody & Lev (2000) suggest that R&D investments lead to some degree of market inefficiency due to information asymmetries to support the investor fixation view. They find that R&D is positively associated with higher insider gains. According to them asymmetric information leads to insider gains in particular with R&D intensive companies. Barth & Kasznik (1999) make a similar finding by studying share repurchases. They find a positive relation between increases in intangibles and the share repurchase announcements likelihood. Kallunki, Nilsson & Helsström (2009) bring out also other motives for insider trading than the exploitation of private information. Those other motives include the need for private portfolio rebalancing and tax planning. However, they do not exclude behavioral biases like previously discussed overconfidence or disposition effect. They suggest that insider selling information can be exploited when insiders take a greater risk, which is a greater proportion of their own wealth allocated on their own company stock.

The earnings fixation is based on the fact that company net earnings have the highest information value for investors of all the company financial figures. Net earnings
show the company’s profit after the company has fulfilled its obligations to its stakeholders. The reason why net earnings are so much favored by investors relates to the easiness of use and the anticipated close relation to a company’s money generating activities. That is why net earnings are used in different valuation models to evaluate company value. Current and past earnings are commonly seen as the best predictor of future earnings. However, the development of accounting standards can have an impact on the value relevance of earnings.

Dichev (2008) discusses how academic research has shown the movement towards balance sheet orientation to have effect on increased earnings volatility and fallen persistence on earnings. Another concern is the reliability of the earnings figure. Disclosed earnings might not reveal the true performance of the firm, since they can be manipulated by the management. Penman & Zhang (2002) argue that the earnings are manipulated, which has an effect on the earnings quality.

When looking from the stock mispricing point of view, the earnings quality and investor fixation are closely related. If investors fixate on earnings and the earnings do not reveal the true performance of the firm, poor earnings quality leads to misevaluation of the stock price. Changes in the accounting principles have been seen to result in bad earnings quality (Healy & Wahlen 1999). The companies might create temporary reserves to be reversed later or temporarily increase earnings by reducing the estimates of the valuation reserves.

However, valuation issues may arise even when companies do not change their accounting principles and qualify with conservative accounting practices. With R&D investments previously discussed temporary reserves are created as a rule. Penman & Zhang (2002) discuss the problems that conservative accounting introduces with R&D intensive companies. They show that growth in R&D investments reduces earnings whereas a fall in R&D investments increases earnings. If these changes are temporary, conservative accounting leads to lower quality of earnings. When the R&D investment level is high, the changes in investments have bigger effect on the net earnings.
1.4 R&D Intensity and Stock Returns

Studies of R&D investments and market performance can be divided into two general categories. The first category includes the studies which concentrate on R&D intensity and market performance. The second category covers the studies which explore the changes in the R&D intensity level. The second category studies differ from the intensity studies because the changes in the R&D intensity level result from managerial decisions. These decisions are rarely publicly announced and are investment decisions. According to Eberhart et al. (2004), investment decisions should not include a timing motive for managers. A significant number of studies have investigated R&D and stock returns since the year 1974 when data from R&D expenses became available.

Early studies of the R&D intensity level and stock markets are concentrated on the U.S. market. Hirschey (1982) find positive effects of R&D on market values. He explores advertising and R&D expenses together. He uses market valuation approach regressed on R&D divided by fundamentals. Chauvin & Hirschey (1993) follow Hirschey (1982) with similar findings. Similar to Hirschey (1982), Bublitz & Ettredge (1989) study R&D and advertising with market reaction model. They suggest that sign and magnitude of the R&D forecast error and abnormal returns can provide information of the expected duration of benefits arising from these activities. They further state that the benefits from advertising are short-lived, while the benefits from R&D are long-lived.

Bublitz & Ettredge’s (1989) finding about long-lived R&D benefits is supported by Sougiannis (1994), who finds R&D benefits lasting for seven years. He shows that a one-dollar sacrifice on R&D expenditures leads to a five-dollar increase in market value. He divides subsequent R&D effect into indirect and direct effect. Indirect effect affects market values through earnings. In the direct effect new information from R&D affects share prices directly. According to Sougiannis (1994), the indirect effect is greater than the direct effect. This implies that R&D information affects share prices more through earnings than information directly from R&D itself. The
finding can be seen to support the earnings fixation because markets seem to rely more on earnings than on information about R&D.

Lev & Sougiannis (1996) document positive relation between firms’ R&D capital and subsequent stock returns after controlling for common risk factors. They also estimate the useful life of R&D capital over different industries. According to Lev & Sougiannis (1996), the useful life of R&D capital varies between five to nine years. The finding is later supported by Amir et al. (2007) with the useful life varying from five to seven years.

Lev, Nissim & Thomas (2007) use different assumed R&D lives from one to eight years. Also, they note that the useful life of R&D capital varies across industries. Contrary to Lev & Sougiannis (1996) and Amir et al. (2007), they suggest that the capitalization and amortization of R&D would improve the information value of financial statements in some industries, but not all. According to them, in those industries stock markets systematically undervalue expensed R&D investments (Lev, Nissim & Thomas 2007).

Accounting rules in Australia provide a unique environment to study R&D expensing versus capitalization of R&D. Australian accounting rules allow companies to decide which method to use. Chan, Faff, Ghargori & Ho (2007) study ‘capitalizers’ and ‘expensers’ and find that the firms which expense their R&D outperform those which choose to capitalize. According to Chan et al. (2007), the possibility to select the method gives some valuable (inside) information to investors about the risks related to the R&D investments. They also suggest that higher R&D intensity is positively correlated with firm performance, regardless of the accounting method used.

Chan et al. (2001) study the risk-adjusted stock returns of firms classified to portfolios by the R&D intensity. They find no evidence of a direct link between R&D expenses and future returns. In their study the average return for R&D portfolios was comparable to the return of stocks with no R&D. The strongest signs of association between R&D intensity and stock returns they find for high R&D to
market value of equity firms, which they show to be mostly past losers. On our study we concentrate on this finding. We will start developing our strategy with the same R&D intensity measures and portfolio compositions. Similar to Lev (1994) and Chan et al. (2001), Chambers et al. (2002) show the positive relation of R&D intensity level and its changes to excess stock returns lasting up to 10 years.

Anagnostopoulou & Levis (2008) find that R&D intensity contributes to company performance only when a firm needs to invest in R&D because of the industry in which it operates. They show that excess stock return persistence is positively dependent on R&D intensity. The return persistence applies especially to the highest R&D intensity firms. Kallunki, Pyykkö & Laamanen (2009) extend this field of studies. They study how the technology-oriented mergers and acquisitions effects on R&D spending related stock valuation. They show that only in the case of technology mergers the acquirers’ stock owners can benefit by the increase of the company market value.

Ciftci, Lev & Radhakrishnan (2009) study R&D intensive companies’ excess returns dividing companies by industry-adjusted R&D intensity. They show that high industry-adjusted R&D intensity firms’ excess returns converge to the excess returns of low R&D intensity firms after five years. They suggest this returns reversal to be a consequence of mispricing. We are going to follow Ciftci et al. (2009) when enhancing the investment strategy. We further lean on the findings that R&D returns are industry-related (Lev et al. 2007, Anagnostopoulou & Levis 2008). We construct similar industry-specific portfolios with Ciftci et al. (2009). Our purpose is to find the industries where the R&D-related returns are the strongest.

Eberhart, Siddique & Maxwell (2004) study significant R&D increases. They show a positive and persistent stock return relation after significant increases in R&D spending. They use Fama-French factor model regressions to show positive abnormal risk-adjusted returns for the five-year period after the R&D increase. Ali, Ciftci & Cready (2012) further show that returns to R&D increases are concentrated on subsequent earnings announcements. The finding suggests that abnormal returns are
at least partly due to mispricing because returns at risk should not concentrate heavily on the announcement dates (Ali et al. 2012). The opposite results are found by Chan et al. (2010) when studying R&D reductions and Saad & Zantout (2011) with excessive R&D investments.

According to Chan et al. (2010) and Saad & Zantout (2011), the negative abnormal returns result from the company’s aggressive risk-taking and failure to control the risks. The risk of new R&D projects rises especially when the company has excessive resources. The overinvestment hypothesis states that companies overinvest in tangible and intangible assets when being in good financial condition. The hypothesis builds on the foundation of the agency theory and managerial discretion. The agency theory explains why managers, tend to overinvest when they have more money to spend. Jensen (2005) calls this the agency cost of free cash flow’. The problems with management control can be mitigated with the development of the company’s corporate governance practices.

Corporate governance has emerged to protect stockholders’ wealth from managerial misuse. Jensen (2005) explains how poor corporate governance practices might lead company officers to destroy part of the company core value. According to Jensen (2005), officers destroy the company value because they try to maintain stock overvaluation by any means. The reason behind this is managerial incentives, which are usually tied to stock performance. If the companies overinvest and the investors are unable to detect the overinvestment, it leads the stock to be overvalued and eventually to depress stock returns.

The risk of poor corporate governance practices to penalize investors is higher when the company needs to maintain a high level of investments. This applies especially to high R&D intensity companies. The problems are more severe when previous R&D investments have been successful and yielded high returns. In that case returns from the investments contribute greatly to the financing of the future R&D projects. This leads outside monitors, debtors and credit rating agencies to have less interest in and controlling power over the company assets.
Jensen (1993) writes in this context about the difficulty of exit. He argues that company officers are blinded to see the states of the economy and industry. Officers therefore continue with high bets even though the industry profits are decreasing due to competition. At the greatest risk are companies which have for a long time experienced growth, high market share, high cash flows and profits. Jensen (1993) emphasizes the organization culture and management mindset to be the main obstacles why the exit decisions cannot be made.

A company’s board has the advising and controlling role. The board defines the strategy to be implemented and selects and monitors executives to implement it. Corporate governance practices have therefore an effect on strategic decision-making and its efficient implementation. Good corporate governance may then affect company performance through competitive strategy implementation, which Porter (1985) sees as a key factor to success. However, we don’t assess this dimension of strategy implementation and leave it for further study.

1.5 Research Problem

This study follows the R&D intensity and stock return related research. Chan et al. (2001) serves as a reference study whose methods are applied. We start by replicating part of the Chan et al. (2001) study with 16 years more data. In Chan et al. (2001) the main finding is that the highest R&D intensity portfolios earn excess returns after controlling for common risk factors. They further find that these stocks tend to be past losers. The purpose of the replication part is to see if the Chan et al. (2001) results hold over a longer period. The replication part of our study tests the first (H1) hypothesis

H1: R&D intensity (measured by R&D expenses to market value of equity) has explanatory power over stock returns
We continue to explore R&D intensive stocks in different industries to find the industries that have positive risk-adjusted excess returns. We construct industry-dependent R&D intensity portfolios to study our second hypothesis (H2), which is based on Anagnostopoulou & Levis’s (2008) and Lev et al. (2007) findings. They show that R&D has value relevance only among R&D intensive industries. Our second hypothesis relates this suggestion.

H2: R&D intensity (measured by R&D expenses to market value of equity) has explanatory power over stock returns only among the high R&D intensity industries.

One explanation for an R&D intensive company’s success is the strategy. In this sense the study is related to Ciftci, Lev & Radhakrishnan (2009). They study R&D intensity, company strategy and stock returns in the framework of leaders and followers. Ciftci et al. (2009) classify companies which invest in R&D over the industry mean as the leaders and companies which invest less than the industry mean as the followers. They show that industry leaders earn higher positive excess returns than followers. Our study evaluates R&D intensive company stock excess returns in Porter’s competitive advantage strategy framework. Similar to Ciftci et al. (2009), Porter’s framework requires study companies at an industry level. The strategy view in this study differs from Ciftci et al. (2009), although their leader follower framework can also be connected to Porter’s ideas (1985, 181-182).

Lastly, we construct a simple proxy for competitive strategy and examine R&D intensive companies’ stock returns and the strategy they choose. Our aim is to improve the investment strategy shown in Chan et al. (2001). The investment strategy is enhanced by combining the industry R&D intensity portfolios and the strategy proxy. The strategy approach is similar to Ciftci et al. (2009) but applies a different strategy proxy. Ciftci et al. (2009) use 48 different industries when calculating the median R&D intensity of the industry. In this study industries will be divided into 10 different industries determined by CRSP database SIC codes and strategy is determined by DuPont identity components.
The strategy division tries to mimic Porter’s generic competitive strategies. Porter (1985, 11-26) divides company competitive strategies into cost leadership and product differentiation. He argues that the selection of competitive strategy is vital for the companies to survive the industry competition. Porter suggests that firms must pursue one of the two strategies to be a market leader. According to Porter, companies which are not able to choose a strategy will be stuck in the middle and suffer from low profitability. In this sense the strategy proxy aims to single out especially the companies with poor performance.
2 R&D INTENSITY AND COMPANY STRATEGY

2.1 Measures of R&D Intensity

According to U.S. accounting rules, R&D costs, with the exception of software development costs, must be expensed (FASB 1974, 1985). Information about R&D expenses allows different determinations of R&D intensity. R&D expenses are commonly measured relative to total sales, earnings, total dividends, book value of equity or market capitalization.

One way to measure R&D and its benefits is to capitalize R&D expenses and calculate yearly amortization from R&D capital. Company performance measures can then be regressed with the R&D capital or the yearly amortization values. According to Lev & Sougiannis (1996), this method is value relevant for investors since it leads to more precise estimates of subsequent stock prices. Studies concentrating on R&D and stock returns have been using this capitalization method as common practice.

Equation (1) follows Lev & Sougiannis’s (1996) R&D capital estimation. In Table 1 the stock of R&D capital is calculated using R&D expenses from previous five years.

\[
RDC_t = RD_u + 0.8 RD_{u-1} + 0.6 RD_{u-2} + 0.4 RD_{u-3} + 0.2 RD_{u-4}
\]  

(1)

where,

- \( RDC_u \) = R&D capital
- \( RD_u \) = R&D expenses

Table 1 shows the R&D intensity development over time and the amount of estimated R&D capital as a percent of book value. The sample is all the companies listed on NYSE, AMEX and NASDAQ with data on the Compustat files from the years 1975-2010. The importance of R&D as intangible capital can be seen as a high partition of R&D capital of book value in Table 1. In the year 2010 the R&D capital accounts for 25.4 % of the total book values.
Table 1. Intensity of Research and Development Activity for all Firms in the U.S.

<table>
<thead>
<tr>
<th>Year</th>
<th>Sales</th>
<th>Earnings</th>
<th>Dividends</th>
<th>Book Value</th>
<th>Market Cap.</th>
<th>R&amp;D Capital as Percent of Book Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1975</td>
<td>1.7</td>
<td>37.0</td>
<td>87.3</td>
<td>4.1</td>
<td>2.8</td>
<td>-</td>
</tr>
<tr>
<td>1980</td>
<td>1.8</td>
<td>35.3</td>
<td>90.4</td>
<td>5.0</td>
<td>3.2</td>
<td>12.5</td>
</tr>
<tr>
<td>1985</td>
<td>3.0</td>
<td>80.4</td>
<td>140.5</td>
<td>7.8</td>
<td>4.4</td>
<td>20.6</td>
</tr>
<tr>
<td>1990</td>
<td>3.3</td>
<td>77.3</td>
<td>145.9</td>
<td>9.2</td>
<td>4.0</td>
<td>25.2</td>
</tr>
<tr>
<td>1995</td>
<td>3.8</td>
<td>70.8</td>
<td>156.8</td>
<td>10.8</td>
<td>2.9</td>
<td>28.5</td>
</tr>
<tr>
<td>2000</td>
<td>4.7</td>
<td>94.7</td>
<td>226.9</td>
<td>9.9</td>
<td>1.2</td>
<td>26.3</td>
</tr>
<tr>
<td>2005</td>
<td>4.3</td>
<td>60.6</td>
<td>140.3</td>
<td>9.0</td>
<td>2.3</td>
<td>25.7</td>
</tr>
<tr>
<td>2010</td>
<td>4.6</td>
<td>50.1</td>
<td>165.6</td>
<td>8.6</td>
<td>2.7</td>
<td>25.4</td>
</tr>
</tbody>
</table>

(Source: Compustat / Crsp)

Overall, R&D intensity development has increased over time by all the measurement figures. In the 35 years from 1975 to 2010 R&D intensity has doubled or tripled depending on the R&D measure used. In the year 2000 R&D intensity was at its peak. It took 10 years to get back to the same level after the year 2000 tech bubble burst. The R&D expenses to sales measure shows how much of current income a company is willing to invest in R&D activities. The R&D to earnings ratio shows how much company owners are willing to sacrifice from their profits on R&D. In the short run, with less R&D companies could deliver more to their shareholders. However, this behavior is not common among R&D intensive firms. R&D intensive firms tend to pay low dividends. In the year 2010 companies invest 1.66 times more in R&D than they pay dividends.

R&D capital to book value is the most stable measure. This follows partly from the fact that dividends, earnings and sales are prone to managerial discretion. R&D to market capitalization is the only measure of these five with direct dependence on the market valuation of the company stock. Table 1 shows some slight differences between measures and their development over time. For example, from the year 2005 to 2010 the R&D to sales ratio has increased while the R&D to earnings measure has decreased. Different measures may thus lead to different results when used in estimations.
2.2 R&D Intensity by Industries

R&D has a different role in different industries. Some industries are focused on inventing new products while other industries refine the production processes. Also, patent protection effectiveness varies between industries. This might have an effect on companies’ willingness to sacrifice dollars on R&D.

Table 2 shows the industry classification and industry definitions by Fama and French which are available on Kenneth French’s web page in his data library. The Compustat SIC code definitions for each industry are described in Appendix 1. We apply these industry classifications when studying R&D intensity and stock return relations in different industries.

Table 2. Industry descriptions

<table>
<thead>
<tr>
<th>Industry Number</th>
<th>Short Name</th>
<th>Industry Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>NoDur</td>
<td>Consumer Non-Durables - Food, Tobacco, Textiles, Apparel, Leather, Toys</td>
</tr>
<tr>
<td>2</td>
<td>Durbl</td>
<td>Consumer Durables - Cars, TV’s, Furniture, Household Appliances</td>
</tr>
<tr>
<td>3</td>
<td>Manuf</td>
<td>Manufacturing - Machin, Trucks, Planes, Chemic, Off Furn, Paper, Com Print</td>
</tr>
<tr>
<td>4</td>
<td>Enrgy</td>
<td>Oil, Gas, and Coal Extraction and Products</td>
</tr>
<tr>
<td>5</td>
<td>HiTec</td>
<td>Business Equipment - Computers, Software, and Electronic Equipment</td>
</tr>
<tr>
<td>6</td>
<td>Telcm</td>
<td>Telephone and Television Transmission</td>
</tr>
<tr>
<td>7</td>
<td>Shops</td>
<td>Wholesale, Retail, and Some Services (Laundries, Repair Shops)</td>
</tr>
<tr>
<td>8</td>
<td>Hlth</td>
<td>Healthcare, Medical Equipment, and Drugs</td>
</tr>
<tr>
<td>9</td>
<td>Utils</td>
<td>Utilities</td>
</tr>
<tr>
<td>10</td>
<td>Other</td>
<td>Other - Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainm, Finance</td>
</tr>
</tbody>
</table>

(Source: Kenneth French Data Library)

Figure 1 shows the development of the industry R&D intensity over time from the year 1975 to 2011. The development between industries differs, only a couple of industries dominate the R&D spending. There is only one industry which has increased its R&D intensity significantly after the year 2000, which is healthcare. Two of the most R&D intensive industries in the year 2011 are healthcare and hitec. These two industries have been the most R&D intensive industries for the whole period.
Figure 1. R&D to sales ratio in different industries (1975 – 2011).

A comparison of Table 1 and Figure 1 shows that hitec and healthcare industries are consistently above the mean R&D intensity of all industries. From Table 2 we see that healthcare industry also includes companies from medical equipment and drugs. Hitec industry includes companies from the fields of business equipment, computers, software and electronic equipment.

The competitive environment between the industries differ which leads the useful life of R&D to vary between industries (Amir et al. 2007; Lev et al. 2007). This fact makes it reasonable to study R&D intensive companies by the industry. The industry profit structure might change over a long period of time and excess profits might move from one industry to another. Porter calls this industry structural change. According to Porter, the structural change is dominated by technological innovations. These technological innovations are created by investments on R&D. (Porter 1980, 177).
2.3 Porter’s Competitive Strategy

Our study builds an investment strategy, which concentrates on R&D intensive stocks. This investment strategy is enhanced by cutting R&D intensive portfolios to half by utilizing Porter’s (1985) competitive strategy framework, which we briefly discuss next.

Porter (1985, 11-26) defines generic competitive strategies, namely cost leadership and product differentiation. According to Porter, the selection of competitive strategy is the key to survive the industry competition. The cost leadership strategy includes different activity choices than differentiation. In contrast to cost leadership, there might be more than one successful differentiation strategy.

In Porter’s famous framework, five forces determine a firm’s ability in an industry to earn return on investment. The firm needs the return on investment to be excess of the cost of the capital to prevail. The five forces are industry competition, suppliers’ and buyers’ bargaining power, threat of new entrants and substitutes. According to Porter (1985), these five forces determine the industry profitability because they influence prices, costs and the required investments of a firm in an industry. Firms that fail to pursue a generic strategy gain no competitive advantage and fall below industry average performance. Porter argues that the firms get stuck in the middle because they are unable to make strategic choices. However, some firms succeed in pursuing more than one strategy. On the one hand, these companies can be extremely successful. On the other hand, they are in danger of getting the stuck in the middle, if business units are not strictly separated. (Porter 1985, 16-20).

Slipping out of the strategy depends on management organization. A strategy requires constant discipline and clear communication. Managers at the lower level might lack confidence to maintain the strategy. When companies target operational efficiency, many managers fail to understand the need for a strategy. If this happens at the same time with rapid growth of the company, the company often loses the original focus. Porter (1996) calls this a growth trap. Also, poor corporate
governance practices may ruin the strategy implementation ability (Jensen 1993). With poor corporate governance practices, the company is more likely to suffer from managerial discretion and the executives looking after their own interests might harm the strategy implementation.

Economic theory states that industry demand and supply conditions define the excess profits available in an industry. Along with industry structure, the demand and supply condition affects a firm’s generic strategy choice. All industries do not offer equal opportunities for sustained profitability. According to Porter, competitive strategy attempts to shape the environment in a firm’s favor. When the competition is fierce, companies might focus more on the short-term survival. In these cases company cost leadership strategy may ruin the industry profitability unless it is based on technological innovation.

Porter (1980) explains industry profits with his five forces model. In Porter’s model entry and exit barriers define the profits available in each industry. These barriers can be based on R&D invention or economies of scale. High entry barriers and low exit barriers lead to high profits within an industry. The industry profits are the lowest when an industry has low entry barriers and high exit barriers. In some industries there is no room for product differentiation strategy. In those industries profits are divided by cost efficiency. However, industry structure shifts gradually over time and companies need to revise their strategies from time to time. Porter (1980, 22).

Diffusion of knowledge lowers the barriers for entry. For example, China has been a follower in the high tech industry and benefitted from its role. Diffusion of knowledge has transformed the related industries to be less profitable. A good example is the telecom industry at the turn of the century. Vice versa, economies of scale in R&D for complex technologies raise the barriers for entry (Porter 1985, 16-20). This might give one explanation for the scale effects in R&D found by Hand (2002) and Ciftci & Cready (2011).
A company utilizing high technology or making high-level R&D investments does not guarantee high profitability. Technology is important for competition if it significantly affects a firm’s competitive advantage or industry structure. In many firms R&D programs are driven more with technological focus than taking the competitive advantage into account. One good example of this was the mobile phone manufacturer and developer Nokia, which made technically cutting-edge products but lost customer focus. However, pioneers of major innovations may gain competitive advantage. Companies which invest heavily in R&D are often seen as pioneers in their industries. Introducing a significant technological innovation can allow a firm to lower costs or enhance differentiation. With the investment strategy enhancement we focus on this point by combining the cost leadership or differentiator firms with high R&D. (Porter 1985, 11-26).
3 DATA AND METHODOLOGY

3.1 Data Description

All the financial information is taken from the Compustat active and research files. The sample is all the companies listed on NYSE, AMEX and NASDAQ with data on the Compustat files. The data consists of the fiscal years from 1975 to 2011. The yearly data has 206 936 and monthly data 2 485 393 observations. The market value of common equity is calculated by multiplying price per share and number of shares outstanding. The price and return data is taken from the CRSP stock return files. The data consists of the following data items: 6 – Total Assets, 12 – Sales, 21 – Dividends, 24 – Price Close, 25 – Common Shares Outstanding, 41 – Cost of Goods Sold, 46 – Research and Development Expense, 60 – Common / Ordinary Equity, 172 – Net Income, 180 – Total Liabilities, 324 – Standard Industrial Classification.

The data may suffer from a series of potential biases, which are briefly discussed below. These biases may have an effect on the results shown in chapter 4, which the reader needs to be aware of.

One potential bias arises from the fact that all R&D firms don’t report R&D. This may happen when companies report their research-like expenses as part of other expenses. This causes the sample of R&D intensive companies to be smaller than actual population. These companies are most probably low R&D intensive stocks, which are here falsely accounted as non-R&D stocks.

The other problem with the data is introduced when the data is imported from various sources and time periods. The data was taken at three different parts from two different databases and then combined together. In addition the return data was taken from a third database. This process has caused some unqualified observations in the data. The duplicate observations were identified by having two monthly entries for the same company identifier. These duplicate entries were deleted.
The data may suffer from survivorship bias. This bias rises when companies which have failed no longer exist in the data. Existing survivorship bias causes results to skew to the right because only the companies that survive to the end of the period are included. Survivorship bias can be reduced by using CRSP delisting data. The reference study by Chan et al. (2001) utilizes this data in their research, while our data does not. CRSP delisting returns corrects the data for companies that disappear from the data for different reasons. (Center for Research in Security Prices 2001).

By utilizing the CRSP delisting data researchers can improve accuracy, integrity and completeness of the CRSP equity data. The delisting categories include merger, exchange of stock, liquidation and poor performance. These categories are further divided by different delisting codes. The empirical results may be biased if the missing returns are not properly accounted. (Center for Research in Security Prices 2001).

The average delisting returns are skewed to the left. For example, the NASDAQ poor performance category has an average delisting return from -11.5% to -19.7% depending on the delisting code. The delisting returns for NYSE and AMEX stocks are higher and negative, from -26.3% to -61.7%. Leaving the delisting returns aside, our positive excess returns are higher compared to Chan et al. (2001). However, the CRSP delisting is not complete and still missing a significant number of delisting data. (Center for Research in Security Prices 2001).

R&D expenses are reported to the Compustat database on a yearly basis for the period 1975-2011. It follows that R&D intensive portfolios can only be reconstructed a yearly basis. More frequent R&D data might result in better fitting results with time series regressions.
3.2 R&D Intensity Definition

Chapter 2.1 presented different R&D intensity measurements. Our definition of R&D intensity is the one which Chan et al. (2001) found to be the most value relevant for investors. That is R&D expenditures to market value of equity. They calculate R&D expenditures with straight line amortization of R&D capital following Lev & Sougiannis (1996). The R&D expenditure calculation is shown in Equation (2). R&D capital calculation was shown in Equation (1).

\[ RE_{it} = 0.2 \left( RDC_{it-1} + RDC_{it-2} + RDC_{it-3} + RDC_{it-4} + RDC_{it-5} \right) \]  

(2)

where,

\( RE_{it} \) = R&D expenditures

\( RDC_{it} \) = R&D capital

Chan et al. (2001) argue that R&D expenditures to sales do not forecast future returns. However, they show that R&D expenditures to market value strongly forecasts future returns. Equation (3) shows their reasoning about the relationship.

\[ \frac{RE}{Mcap} = \left( \frac{RE}{Sales} \right) \cdot \left( \frac{Sales}{Mcap} \right) \]  

(3)

where,

\( RE \) = R&D expenditures

\( Sales \) = Company sales

\( Mcap \) = Market value of company equity

Equation (3) suggests sales to market effects to be stronger for high R&D to sales firms. We use R&D expenditures to market capitalization as an R&D intensity measure when sorting portfolios. The portfolio sorting techniques and methods of studying excess returns are discussed on the next chapter.
3.3 Portfolio Sorts and Control Portfolios

Control portfolios try to capture the common return-affecting characteristics such as size and book to market. Also, industry-specific control portfolios can be used. For the U.S. stock market, a wide selection of control portfolios is available on the Kenneth French web pages. The offered portfolios do not include a hold range and ignore transaction costs. The portfolios include all NYSE, AMEX and NASDAQ firms. The breakpoints only use NYSE firms. The abnormal return for a stock for a specific month (year) equals its return for the month (year), minus the return of the corresponding reference portfolio for the specific month (year).

The Fama-French 5 x 5 control portfolios are constructed at the end of June, at the intersections of five portfolios formed on size and five portfolios formed on the ratio of book equity to market value. The size breakpoints for year \( t \) are the NYSE market equity quintiles at the end of June of \( t \). Book to market for June of year \( t \) is the book equity for the last fiscal year end in \( t-1 \) divided by market equity for December of \( t-1 \). The book equity to market equity breakpoints are NYSE quintiles.

When we replicate the study by Chan et al. (2001), the difference is the usage of 5 x 5 control portfolios taken from Kenneth French’s web pages instead of constructing 6 x 5 control portfolios they use. Chan et al. (2001) try to control the small (tiny) stock effect creating their own control portfolios by cutting the smallest-size portfolio in half. They use these 6 x 5 size, book-to-market control portfolios while exploring R&D intensive portfolios and their excess returns.

The Fama-French 10 industry portfolios are constructed from NYSE, AMEX and NASDAQ stock by Compustat four-digit SIC codes, see detailed industry classification in Appendix 1. If a Compustat SIC code is not available, the CRSP SIC code is used. The Construction is done at the end of June each year. Returns for industry portfolios are calculated from July of year \( t \) to June of year \( t+1 \).
For the time period 1975-2011 R&D expenses are reported to the Compustat database a yearly basis. It follows that R&D intensive portfolios can be reconstructed yearly. However, quarterly R&D expenses are available from the year 1987. Because we need to focus on the replication part on the yearly expenses, we leave the quarterly data for further study. Stocks are divided into five equally sized portfolios by R&D intensity. In addition to these five portfolios, a separate portfolio for non-R&D stocks is created. The Non-R&D stocks include companies which either do not report their R&D expenses or report zero R&D expenses. We use R&D expenditures to market value of equity as a measure of R&D intensity, see chapter 3.2. The R&D intensity is calculated using the end of year value of the R&D expenditures. Portfolio returns and excess returns are calculated over the one to five years after the portfolio formation.

The study employs two-way sort similar to Chan et al. (2001). Two-way portfolio sorts are used to sort R&D intensity portfolios with past three year returns. R&D intensity portfolios are cut in half by past three year returns. The purpose is to explore if return reversal explains the presumably high returns of R&D intensive stocks. Two-way portfolio sorts are also used with industry portfolios and the developed investment strategy. When the investment strategy is enhanced with the Porter’s strategy approach, portfolios are sorted by R&D intensity and cut in half by the developed strategy proxy, see chapter 3.5. The idea is to improve the excess returns by better selecting the R&D intensive stocks on the long and the short portfolios. If successful, the sorting leads to higher excess returns and higher information ratios.

Intercept only regressions are used with both Fama-French 5 x 5 and 10 Fama-French industry control portfolios. With the time series regression, we employ risk factor models, which are presented in the next chapter. With the control portfolios, we calculate the mean return over the control portfolio return. We call this return excess over size/book-to-market or industry portfolio return. The used ordinary least square regression equation without predictors is described in Equation (4).
\[ Y_i = a + \varepsilon_i \] (4)

where,
\( Y_i \) = Response variable
\( a \) = Intercept
\( \varepsilon_i \) = Error term

To reduce problems with heteroskedasticity, there are two choices. The first choice is to transform the data so that the Gauss-Markov conditions are met. Second choice is to disregard efficiency and apply ordinary least squares, and fix the error terms. We apply the latter one with the use of the Newey-West error correction method. Newey-West method is a simplification of the error term correction problem. The simplification is founded on the fact that observations are more correlated with each other the closer they are. Instead of estimating all the covariances in the error terms, Newey and West suggest estimating only the most important covariances. (Hill, Griffits & Lim 2011, 356-358).

The Newey-West error correction method provides serial correlation consistent standard errors. The method requires selecting the distance/lags after which the correlations can be ignored. However, it has some drawbacks. First, the ordinary least square is not efficient. There exists an unbiased linear estimator with a lower variance. Second, the number of lags to include in the model needs to be selected beforehand. As a result of Newey-West error correction, the standard errors are larger than the uncorrected ones. (Hill, Griffits & Lim 2011, 356-358).

SAS software’s proc model offers a kernel option with the GMM estimator in the fit statement to correct standard errors for heteroscedasticity and autocorrelation. Kernel option Bartlett corresponds to the Newey-West estimator. The Newey-West standard errors should be calculated conditional on a choice of maximum lag. The proc model, however, does not offer an option to determine the maximum lag length which needs to be given beforehand. The maximum lag must be set to be large enough so that autocorrelations at lags longer than lag length are small enough to ignore. We select the lag to be large enough depending on the length of the excess return estimation.
3.4 Factor Models

Factor models are used to compare different investment strategies. These models try to account for the risks attributed to an investment strategy. In the factor models the explained variable is the excess return. Excess return is calculated over risk-free asset return, which we use as the three-month U.S. Treasury bill rate. In an efficient market where information is available to everybody at no cost, excess returns should not persist after accounting for all the factors which affect returns. Intercept terms or alphas presented by factor models are called risk-adjusted excess returns. Alpha indicates the average amount of excess return that is not explained by the risk factors.

Factor models use explanatory variables, which are constructed based on criticism of Sharpe’s CAPM (1964). Banz (1981) found that Sharpe’s CAPM does not explain small companies’ stocks returns in the time period 1936-1975. Fama-French (1993) extended Sharpe’s CAPM to include size and book to market factors. Book to market factor try to correct CAPM failure to price value stocks because these assets have high average returns but low estimated betas. Equation (5) defines the three-factor model used by Fama & French (1993).

Carhart (1997) shows that momentum effect drives the mutual funds excess returns. He adds a fourth factor, momentum, to the Fama-French three-factor model. Momentum was presented to explain the high stock returns by Jegadeesh and Titman (1993, 2001). Momentum effect is found to be one of the most persistent market anomalies (Fama & French 2008, 2010). Equation (6) defines the Carhart (1997) four-factor model.

Equation (7) defines the five-factor model used by Chan et al. (2001). They include a fifth factor, reversal, in their R&D intensive stocks time series regressions. The use of the reversal factor is justified by the results that suggest the highest R&D intensive portfolios having depressed returns in the past.
Equations (5), (6) and (7) represent the three-, four- and five- factor model used in this study to evaluate R&D intensive portfolios.

\[
R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + \epsilon_{pt} \quad (5)
\]

\[
R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + m_p MOM_t + \epsilon_{pt} \quad (6)
\]

\[
R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + m_p MOM_t + r_p REV_t + \epsilon_{pt} \quad (7)
\]

where,

\( \alpha_p \) = Intercept
\( R_{ft} \) = Risk-free rate
\( R_{pt} \) = Portfolio p’s expected return
\( R_{mt} \) = Market portfolio return
\( \beta_p \) = Portfolio p’s market factor
\( s_p \) = Size factor
\( SMB_t \) = Small stocks minus big stocks (size premium)
\( h_p \) = Book to market factor
\( HML_t \) = Value stocks minus growth stocks (value premium)
\( m_p \) = Momentum factor
\( MOM_t \) = Short term winner stocks minus loser stocks (momentum)
\( r_p \) = Long-term reversal factor
\( REV_t \) = Long-term low return minus short-term high return stocks (reversal)
\( \epsilon_{pt} \) = Error term

In Equations (5), (6) and (7) the \( R_{pt} \) is the portfolio’s return in period t. The \( R_{ft} \) is the three-moth Treasury bill rate, \( R_{mt} \) is the return of the market portfolio, \( SMB_t \) is the size factor premium, \( HML_t \) is the relative price factor premium, \( MOM_t \) is the momentum factor premium, \( REV_t \) is the long-term reversal factor premium. The portfolio \( \beta_p \) indicates its sensitivity to market risk, size coefficient \( s_p \) indicates its sensitivity to size risk, price coefficient \( h_p \) indicates its sensitivity to price risk,
momentum coefficient $m_p$ indicates its sensitivity to momentum risk and reversal coefficient $r_p$ indicates its sensitivity to reversal risk. $e_{pt}$ is the random partition of the portfolio’s excess return which is not explained by the model.

Information ratio is a commonly used measure to evaluate portfolio performance and portfolio manager skill. Information ratios (IR) are reported for all monthly time series regressions. The information ratio tries to summarize the mean-variance properties of an active portfolio. The higher information ratio the higher is the return per unit of volatility. Depending on the purpose, there are different methods to calculate the information ratio. We use an information ratio which is factor model intercept term divided by standard error from regression. We use the information ratio to compare the R&D intensive investment strategies. The information ratio is defined in equation (8). (Goodwin 1998).

\[
IR = \frac{\alpha_{pt}}{std(e_{pt})}
\] 

where,

$IR$ = Information ratio

$\alpha_{pt}$ = Intercept term from factor model time series regression

$e_{pt}$ = Residual term from factor model time series regression

This study applies a stepwise selection method to determine which factor model is the most appropriate when running factor model time series regressions. The selection is done between the presented three-, four- and five-factor models depending on the significance of the factor t-statistic. In the case of investment strategy, if we need to choose between the models, we select the model which gives the lowest alpha. In the step wise selection method each factor model is estimated for each R&D intensive portfolio (within an industry). However, the presented factor models probably do not account for all R&D-specific risks.
With all regressions we first replicate and match the Chan et al. (2001) results to calibrate our code with the time period they used (1975-1995). Then we run the regressions for the time period 1975-2011 and present these results.

### 3.5 Competitive Strategy Proxy

Company strategy is not directly observable and thus an observable proxy must be used. One common measure for company performance is return on equity (ROE). ROE shows how much money a company generates from the money shareholders have invested. ROE can be further broken down with basic DuPont identity to profit margin, asset turnover and financial leverage components, Equation (9). Successful strategy determination will be further determined by these components. (Penman 2010, 372).

\[
ROE = \left( \frac{\text{profit}}{\text{sales}} \right) \left( \frac{\text{sales}}{\text{assets}} \right) \left( \frac{\text{assets}}{\text{equity}} \right)
\]

(9)

where,

\( ROE = \text{Return on equity} \)

\( \text{Profit} = \text{Net income to sales} \)

\( \text{Assets} = \text{Total assets} \)

\( \text{Equity} = \text{Total shareholder’s equity} \)

ROE components serve as a proxy for company strategy selection in the classical Porter model. We hypothesize that in the case of cost leadership strategy, successful companies are likely to have a high asset turnover, but a low profit margin. Successful product differentiators have a high profit margin, but a lower asset turnover and less leverage. We divide companies into two groups. The first group includes the companies which are classified as either cost leadership or product differentiator companies. The second group includes all the other companies, which are in Porter’s words ‘stuck in the middle’.
More specifically, we define the product differentiator companies to be companies which have a profit margin over the industry median. Similar we define cost leadership companies to have an asset turnover over the industry median. The rest of the companies are classified as what Porter calls stuck in the middle companies. The companies have not succeeded in following one of the two strategies. We construct these medians by end of each year within industries and classify companies to belong to one of these three groups. At this point it is noted that we ignore the leverage part by concentrating only on the asset turnover and profitability components. Further we expect these past measures to predict the future performance together with R&D.
4 RESULTS

4.1 The Stock Market Valuation of R&D Expenditures

The study replicates Chan et al. (2001) with 16 years more data. Similar to their study, Table 3 shows R&D to market capitalization sorted portfolio returns. Results from the time period 1975-2011 shown in Table 3 are comparable to Chan et al. (2001) Table IV.

Table 3. Returns of Portfolios Classified by R&D Expenditure Relative to Equity Market Value

Each year from 1975 to 2011, all stocks are ranked by their R&D expenditure relative to equity market value, and assigned to one of five equally sized portfolios. Stocks with no R&D expenditures are assigned to a separate portfolio. The sample includes all NYSE, AMEX and Nasdaq domestic primary issues with coverage on the CRSP and COMPUSTAT files. In Panel A, each portfolio’s average annual buy-and-hold return is reported over the five years prior to portfolio formation; over each year from one to three years after portfolio formation; and averaged over the three postformation years. Panel B reports each portfolio’s average return in excess of the equally weighted return on a control portfolio of stocks matched by firm size and book-to-market in the first through third postformation years. Panel C reports excess returns based on control portfolios matched by firm size and adjusted book equity (book equity plus the value of R&D capital) relative to market equity.

<table>
<thead>
<tr>
<th>Panel A: Returns Before and After Portfolio Formation</th>
<th>1(low)</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5(high)</th>
<th>Non-R&amp;D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average annual return over 5-year period before portfolio formation</td>
<td>0.2538</td>
<td>0.2467</td>
<td>0.2089</td>
<td>0.1598</td>
<td>0.0849</td>
<td>0.1679</td>
</tr>
<tr>
<td>First year after portfolio formation</td>
<td>0.1024</td>
<td>0.1487</td>
<td>0.1700</td>
<td>0.2457</td>
<td>0.2768</td>
<td>0.1671</td>
</tr>
<tr>
<td>Second year after portfolio formation</td>
<td>0.1271</td>
<td>0.1591</td>
<td>0.1995</td>
<td>0.2312</td>
<td>0.2509</td>
<td>0.1659</td>
</tr>
<tr>
<td>Third year after portfolio formation</td>
<td>0.1661</td>
<td>0.1924</td>
<td>0.2015</td>
<td>0.2139</td>
<td>0.2285</td>
<td>0.1676</td>
</tr>
<tr>
<td>Average annual return over 3-year period after portfolio formation</td>
<td>0.1318</td>
<td>0.1667</td>
<td>0.1903</td>
<td>0.2303</td>
<td>0.2521</td>
<td>0.1668</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Excess Returns After Portfolio Formation</th>
</tr>
</thead>
<tbody>
<tr>
<td>First year after portfolio formation</td>
</tr>
<tr>
<td>Second year after portfolio formation</td>
</tr>
<tr>
<td>Third year after portfolio formation</td>
</tr>
<tr>
<td>Average annual return over 3-year period after portfolio formation</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Excess Returns Based on Adjusted Book Value</th>
</tr>
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<tbody>
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<td>First year after portfolio formation</td>
</tr>
<tr>
<td>Second year after portfolio formation</td>
</tr>
<tr>
<td>Third year after portfolio formation</td>
</tr>
<tr>
<td>Average annual return over 3-year period after portfolio formation</td>
</tr>
</tbody>
</table>

(Source: crsp / compustat)
Panel A shows the R&D to market capitalization sorting power to reveal R&D intensive stocks’ high returns compared to low R&D intensity or non-R&D stocks. Compared to Chan et al. (2001), the non-R&D stocks have 2.8 % lower yearly returns. The difference between high and low R&D intensity portfolio three-year average returns is 12.0 % compared to 11.1 % with Chan et al. (2001). Most importantly, Table 3 Panel A shows the long-term reversal nature of the high-intensity portfolio returns. In the highest-intensity portfolio the average annual return for the five-year period prior to portfolio formation is 8.49 % while the first-year return after portfolio formation is 27.68 %.

Panel B reports each portfolio’s average return in excess of the equally weighted return on a Fama-French 5 x 5 size, book to market portfolio in the first through third post-formation years. The three-year average excess returns for the two highest intensive portfolios are 6.37 % and 7.68 % compared to Chan et al. (2001) 2.18 % and 6.12 %. Excess returns for the two highest intensity portfolios are statistically significant for all three years at 1 % level. The non-R&D portfolio excess returns are close to zero and statistically insignificant.

Chan et al. (2001) suggest that if investors are able to adjust financial statements with R&D capital, a firm should be matched with adjusted book to market ratio. Panel C reports excess returns based on control portfolios matched by firm size and adjusted book equity (book equity plus the value of R&D capital) relative to market equity. The three-year average excess returns for the two highest intensive portfolios are 6.05 % p.a. and 6.78 % p.a. compared to Chan et al. (2001) 1.55 % p.a. and 5.39 % p.a. Excess returns for the two highest intensity portfolios are statistically significant for all three years at 1 % level and portfolio 3 has statistically significant positive returns at 5 % level. The non-R&D portfolio’s excess returns are close to zero and statistically insignificant.

The excess returns shown in Panels B and C are relatively high, suggesting that investors are not able to fully value intangibles. Portfolio 4, which is the second highest R&D intensive stocks, shows the largest difference compared to Chan et al.
The reason for the difference is probably the different-size portfolio breakpoints because the high intensity portfolios are populated with smalls stocks. While they construct 6 x 5 size control portfolios, we use the 5 x 5 control portfolios from Kenneth French’s web pages.

The Table 4 reports each portfolio’s average excess return over each of the first three years following portfolio formation, and over all three postformation years. Table 4 two-way sorts strengthen the finding in Table 3 Panel A, the dependency of the highest R&D intensive portfolios and the past returns. Table 4 is comparable to Chan et al. (2001) Table V with the addition of statistical significance of each year’s excess return. Unlike Chan et al. (2001), we use R&D adjusted book-to-market because it shows more clearly the past three-year return reversal for all portfolios. All portfolios with low 3-year past return, show positive excess return at least 1% level except the highest intensity portfolio 5 at third year and portfolio 2 at first year.

**Table 4. Excess Returns of Portfolios Classified by R&D Intensity, and by Past 3-year Return**

Each year from 1975 to 2011, all stocks with R&D expenditures are ranked by R&D expenditures relative to sales, and assigned to one of five equally sized portfolios. The sample includes all NYSE, AMEX and Nasdaq domestic primary issues with coverage on the CRSP and COMPUSTAT files. Within each of the five portfolios, stocks are further ranked by their average rates of return over the prior three years and subdivided into two equally sized groups. The Table reports each portfolio’s average excess return over each of the first three years following portfolio formation, and over all three postformation years. In measuring excess returns, each stock is matched with a control portfolio of stocks based on size and adjusted book-to-market and then past three-year return. The difference is calculated between the stock’s annual buy-and-hold return and the return on the control portfolio.

<table>
<thead>
<tr>
<th>Classification by</th>
<th>Excess Return in Year after Portfolio Formation</th>
<th>Average Excess Return over 3 Post-Formation Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D to sales</td>
<td>Past 3-year return</td>
<td>First Year ** 0.0320</td>
</tr>
<tr>
<td>1 (low)</td>
<td>1 (low)</td>
<td>0.0069</td>
</tr>
<tr>
<td>2 (high)</td>
<td>1</td>
<td>0.0156</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>-0.0047</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>0.0675 ***</td>
</tr>
<tr>
<td>2</td>
<td>-0.0059</td>
<td>0.0052</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0.1071 ***</td>
</tr>
<tr>
<td>2</td>
<td>-0.0091</td>
<td>0.0236 *</td>
</tr>
<tr>
<td>5 (high)</td>
<td>1 (low)</td>
<td>0.1039 ***</td>
</tr>
<tr>
<td>2 (high)</td>
<td>-0.0515 ***</td>
<td>-0.0077</td>
</tr>
</tbody>
</table>

(Source: crsp / compustat, */**/*** = significance at 5% / 1% / 0.1% level)
Table 4 shows clear evidence of the long-term reversal nature of R&D intensity portfolios. The reversal effect is economically the strongest in the two highest intensity portfolios. The interpretation is similar to Chan et al. (2001). Especially the depressed high R&D intensive stocks earn large excess returns over Fama-French size, book-to-market control portfolio returns. The returns for the low past 3-year return portfolios are statistically significant for two to three years.

The difference in the excess returns of the highest intensity portfolio to Chan et al. (2001) is probably due to missing delisting returns. The two highest R&D intensive portfolios have the highest proportion of missing returns. These firms have mostly negative net income, which suggests negative delisting returns. For example, in the year 2000 the highest R&D intensity ranked portfolio had 494 firm observations, of which 40 had missing returns. 34 out of those 40 companies with missing return observations had negative net income. CRSP delisting returns usage would probably correct downwards the two highest R&D intensive portfolio results shown in the Table 3. We mimic the delisting returns with rough estimate of delisting average returns. Usage of the estimate lowered the excess returns about a 1% per annum for the two highest intensity portfolios. Due to the approximate nature of the estimation we don’t show these results here. (Center for Research in Security Prices 2001).

Table 5 presents the monthly time series regression results for one to three years after portfolio formation. Each year from 1975 to 2011, all stocks are ranked by their R&D expenditure relative to the market value of equity. Table 5 is comparable to Chan et al. (2001) Table VI with the addition of zero portfolios and information ratios (IR). Zero portfolios are long-short portfolios where investment strategy goes long on the high intensity portfolio and short on the low intensity portfolio. Replication for the time period 1975-1995 shows slightly different risk-adjusted returns than Chan et al. (2001), these results are not shown. The excess returns for the highest R&D intensity portfolios for 1 to 3 years after portfolio formation were 0.52, 0.47 and 0.55 compared to Chan et al. (2001) 0.55, 0.52 and 0.53 percent in a month. Similar to them, the t-statistics for alphas were statistically significant at 1% level for the two highest intensity portfolios for all three years.
Table 5. Factor Model Regressions for Monthly Returns (in Percent) on Portfolios Sorted by R&D Relative to Market Equity

Each year from 1975 to 2011, all stocks are ranked by R&D expenditure relative to market value of equity, and assigned to one of five equally sized portfolios. Stocks with no R&D expenditures are assigned to a separate portfolio. The sample includes all NYSE, AMEX and Nasdaq domestic primary issues with coverage on the CRSP and COMPUSTAT files. Estimated coefficients, t-statistics, adjusted R², and IR are reported for the five-factor model presented on the equation (7): The model is estimated using monthly returns from each of the first three years following portfolio.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>a</th>
<th>t(a)</th>
<th>b</th>
<th>t(b)</th>
<th>s</th>
<th>t(s)</th>
<th>h</th>
<th>t(h)</th>
<th>r</th>
<th>t(r)</th>
<th>d</th>
<th>t(d)</th>
<th>R²</th>
<th>IR</th>
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<tr>
<td>First year</td>
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<tr>
<td>1 (low)</td>
<td>-0.22</td>
<td>-2.08</td>
<td>1.02</td>
<td>42.45</td>
<td>0.93</td>
<td>23.87</td>
<td>-0.15</td>
<td>-3.56</td>
<td>-0.11</td>
<td>-2.21</td>
<td>-0.33</td>
<td>-14.18</td>
<td>0.90</td>
<td>-0.36</td>
</tr>
<tr>
<td>2</td>
<td>0.12</td>
<td>1.27</td>
<td>1.02</td>
<td>45.30</td>
<td>0.94</td>
<td>26.16</td>
<td>-0.18</td>
<td>-4.59</td>
<td>0.02</td>
<td>0.35</td>
<td>-0.25</td>
<td>-11.56</td>
<td>0.92</td>
<td>0.22</td>
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<tr>
<td>3</td>
<td>0.33</td>
<td>3.07</td>
<td>1.01</td>
<td>40.89</td>
<td>0.95</td>
<td>23.80</td>
<td>-0.15</td>
<td>-3.42</td>
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<td>-0.22</td>
<td>-9.30</td>
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<td>0.54</td>
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<tr>
<td>4</td>
<td>0.66</td>
<td>5.09</td>
<td>1.01</td>
<td>34.37</td>
<td>1.03</td>
<td>21.79</td>
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<td>-7.35</td>
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<td>0.89</td>
</tr>
<tr>
<td>5 (high)</td>
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<td>-0.20</td>
<td>-7.39</td>
<td>0.88</td>
<td>0.79</td>
</tr>
<tr>
<td>5 (high)</td>
<td>0.69</td>
<td>4.05</td>
<td>0.94</td>
<td>24.16</td>
<td>1.13</td>
<td>18.14</td>
<td>-0.09</td>
<td>-1.28</td>
<td>0.13</td>
<td>1.69</td>
<td>-0.22</td>
<td>-5.98</td>
<td>0.80</td>
<td>0.73</td>
</tr>
<tr>
<td>zero</td>
<td>0.47</td>
<td>3.27</td>
<td>-0.05</td>
<td>-1.41</td>
<td>0.32</td>
<td>6.12</td>
<td>-0.10</td>
<td>-1.73</td>
<td>0.07</td>
<td>1.03</td>
<td>0.08</td>
<td>2.75</td>
<td>0.16</td>
<td>0.59</td>
</tr>
</tbody>
</table>

(source: crsp / compustat)
The factor model regression results for the period 1975-2011, show higher statistically significant alphas for high intensity portfolios than for the period 1975 - 1995. Amir et al. (2007) gives one explanation which is a structural break in the data in the mid-80’s. They suggest that companies might be shifting towards more risky R&D strategies after the year 1986. Testing periods 1975-1986 and 1986-2011, we found the alphas to be higher for the later period, these results are not shown. For the period 1975-2011, the alpha for the low intensity portfolio is negative and significant for the first year at -2.64 % p.a. For the high intensity portfolio it is positive and significant at 9.24 % p.a. It follows that the zero portfolio excess return for first year is 11.88 % p.a. with exceptional high information ratio of 1.12.

Information ratios are high for the two highest R&D intensity portfolios varying from 0.71 to 0.89. These ratios are at a very good level (Grinold & Kahn 1992). Information ratios are higher for portfolio 4 than the highest R&D intensive portfolio 5, which implies that the returns for the highest intensity portfolio are more volatile. The highest intensity portfolio has high exposure to small stocks, which probably results in higher volatility. The high excess returns and the high information ratios have strong persistence. Similar to Chan et al. (2001) we test statistically significant excess return for the period 1975 - 2011 to last up to five years. However, the longer window worsens the possible omitted risk factor problems and in further time series regressions and in the investment strategy we continue to concentrate only on the one-year excess returns.

Table 5 shows that factor loadings are statistically significant for almost all portfolios for all three years. Adjusted R² are high, varying from 0.77 to 0.92. A high R² implies that the factors explain the returns well. The size factor loadings for the highest R&D intensity portfolio suggest exposure to small stocks. Notably, for these portfolios the market exposure beta is lower than 1.0 and the value premium is statistically insignificant. The reversal and momentum factors load significantly for the three highest R&D intensity portfolios. On following chapters we focus on these high and low intensity portfolios to develop the investment strategy.
4.2 R&D Intensive Portfolio Returns by the Industries

For the investment strategy enhancement we next identify the industries with the excess returns. Table 6 shows the non-R&D portfolio excess returns over Fama-French 10 industry control portfolios. Among the different industries, the non-R&D portfolios in general do not have statistically significant excess returns. Manufacturing and hitech have negative and statistically significant returns for one year after portfolio formation. Non-Durables have statistically significant 2.44 % yearly return in the third year, but from Table 7 we can see there is not much more story to tell with this industry. The only interesting exception is the industry 7, shops, whose results are positive and statistically significant at 5 % and 1 % level. Persistence in this industry is strong and was tested to last for five years. The shops industry uses less than 1% of the sales for R&D. In the case of the shops industry, one might be interested in the advertising expenses instead of R&D expenses. Due to the insignificance and as previously noted, the non-R&D portfolios are not in the further interest of this study.

*Table 6. Non-R&D Portfolios’ Excess Returns Controlled with Industry Benchmark Portfolios*

Each year from 1975 to 2011, all stocks are ranked by their R&D expenditure relative to equity market value by their industry, and assigned to one of five equally sized portfolios. Stocks with no R&D expenditures are assigned to a separate portfolio. The sample includes all NYSE, AMEX and Nasdaq domestic primary issues with coverage on the CRSP and COMPUSTAT files. Each portfolios average return is shown in excess of the equally weighted return on a control portfolio of stocks matched by Fama-French 10-industry portfolios in the first through third postformation years.

<table>
<thead>
<tr>
<th>R&amp;D-portfolio</th>
<th>Industry</th>
<th>First Year</th>
<th>Second Year</th>
<th>Third Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>non-R&amp;D</td>
<td>1 NoDur</td>
<td>0.0066</td>
<td>0.0126</td>
<td>0.0244 **</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>2 Durbl</td>
<td>-0.0003</td>
<td>0.0116</td>
<td>0.0154</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>3 Manuf</td>
<td>-0.0240 **</td>
<td>-0.0099</td>
<td>-0.0132</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>4 Enrgy</td>
<td>0.0346</td>
<td>0.0273</td>
<td>0.0173</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>5 HiTec</td>
<td>-0.0319 *</td>
<td>-0.0178</td>
<td>0.0148</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>6 Telcm</td>
<td>0.0232</td>
<td>0.0095</td>
<td>0.0131</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>7 Shops</td>
<td>0.0178 *</td>
<td>0.0289 **</td>
<td>0.0358 **</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>8 Hlth</td>
<td>-0.0249</td>
<td>-0.0289</td>
<td>-0.0053</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>9 Utils</td>
<td>-0.0013</td>
<td>0.0003</td>
<td>-0.0008</td>
</tr>
<tr>
<td>non-R&amp;D</td>
<td>10 Other</td>
<td>-0.0036</td>
<td>-0.0010</td>
<td>0.0037</td>
</tr>
</tbody>
</table>

(Source: crsp / compustat, */**/*** = significance at 5% / 1% / 0.1% level)
Table 7 shows the highest and the lowest R&D intensity portfolio excess returns over Fama-French 10 industry control portfolios. In high R&D intensity industries the highest R&D intensity portfolios have statistically significant excess returns over benchmark portfolios. These industries are healthcare, hitec, manufacturing and durables. After controlling for the common risk factors with time series analysis the excess returns disappear in the durables industry. The time series regression results for durables are not shown and the study continues to focus on the three interesting industries, namely healthcare, hitec and manufacturing.

Table 7. Highest and Lowest R&D to Market Capitalization Portfolios’ Excess Returns Controlled with Industry Benchmark Portfolios

<table>
<thead>
<tr>
<th>R&amp;D-portfolio</th>
<th>Industry</th>
<th>First Year</th>
<th>Second Year</th>
<th>Third Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 (High)</td>
<td>1 NoDUR</td>
<td>0.0403</td>
<td>0.0390</td>
<td>0.0246</td>
</tr>
<tr>
<td>5 (High)</td>
<td>2 Durbl</td>
<td>0.0938 *</td>
<td>0.0807</td>
<td>0.0902</td>
</tr>
<tr>
<td>5 (High)</td>
<td>3 Manuf</td>
<td>0.0643 ***</td>
<td>0.0574 ***</td>
<td>0.0530 ***</td>
</tr>
<tr>
<td>5 (High)</td>
<td>4 Energy</td>
<td>-0.0060</td>
<td>-0.0437</td>
<td>0.0061</td>
</tr>
<tr>
<td>5 (High)</td>
<td>5 HiTec</td>
<td>0.1258 ***</td>
<td>0.1019 ***</td>
<td>0.0549 **</td>
</tr>
<tr>
<td>5 (High)</td>
<td>6 Telecm</td>
<td>0.1659</td>
<td>0.1390</td>
<td>0.1145</td>
</tr>
<tr>
<td>5 (High)</td>
<td>7 Shops</td>
<td>0.0634</td>
<td>-0.0060</td>
<td>0.0212</td>
</tr>
<tr>
<td>5 (High)</td>
<td>8 Hlth</td>
<td>0.1248 ***</td>
<td>0.1210 ***</td>
<td>0.0448</td>
</tr>
<tr>
<td>5 (High)</td>
<td>9 Utilis</td>
<td>0.0041</td>
<td>-0.0220</td>
<td>-0.0268</td>
</tr>
<tr>
<td>5 (High)</td>
<td>10 Other</td>
<td>0.0323 *</td>
<td>0.0347</td>
<td>0.0302</td>
</tr>
<tr>
<td>1 (low)</td>
<td>1 NoDUR</td>
<td>-0.0379 **</td>
<td>-0.0297</td>
<td>-0.0311</td>
</tr>
<tr>
<td>1 (low)</td>
<td>2 Durbl</td>
<td>-0.0583 **</td>
<td>0.0162</td>
<td>0.0268</td>
</tr>
<tr>
<td>1 (low)</td>
<td>3 Manuf</td>
<td>-0.0621 ***</td>
<td>-0.0479 ***</td>
<td>-0.0324 ***</td>
</tr>
<tr>
<td>1 (low)</td>
<td>4 Energy</td>
<td>-0.0898 **</td>
<td>-0.0033</td>
<td>0.0565</td>
</tr>
<tr>
<td>1 (low)</td>
<td>5 HiTec</td>
<td>-0.0929 ***</td>
<td>-0.0541 ***</td>
<td>-0.0111</td>
</tr>
<tr>
<td>1 (low)</td>
<td>6 Telecm</td>
<td>-0.0209</td>
<td>0.0076</td>
<td>0.0502</td>
</tr>
<tr>
<td>1 (low)</td>
<td>7 Shops</td>
<td>-0.0354</td>
<td>0.0018</td>
<td>-0.0172</td>
</tr>
<tr>
<td>1 (low)</td>
<td>8 Hlth</td>
<td>-0.1368 ***</td>
<td>-0.0939 ***</td>
<td>-0.0349</td>
</tr>
<tr>
<td>1 (low)</td>
<td>9 Utilis</td>
<td>-0.0152</td>
<td>0.0009</td>
<td>-0.0685 ***</td>
</tr>
<tr>
<td>1 (low)</td>
<td>10 Other</td>
<td>-0.0542 ***</td>
<td>-0.0502 ***</td>
<td>-0.0064</td>
</tr>
</tbody>
</table>

(Source: crsp / compustat, */**/*** = significance at 5% / 1% / 0.1% level)
When turning to low R&D intensity portfolios, manufacturing, hitec and healthcare show interestingly statistically significant negative returns. Manufacturing has the strongest persistence. Persistence in manufacturing lasts for three years compared to two years in hitec and healthcare. In these three industries the non-R&D portfolios reported in Table 6 do not show statistically significant results, except for the manufacturing one-year negative return. Also stocks classified as belonging to non-durables, durables, energy and other industry groups show statistically significant negative returns for one to two years. Since the high intensity portfolio stocks of these industries do not have statistical significance, we leave these stocks untouched.

All the industry time series regressions use monthly return data taken from the CRSP return database. Table 8 shows the monthly excess return in percentage after controlling for risk factors. In Table 8, b is the market factor estimate, s is the size factor estimate, h is the book to market factor estimate, r is the reversal factor estimate, m is the momentum factor estimate and $R^2$ is the model’s adjusted R-squared. Pastor and Stambaugh (2003) suggest liquidity to be an important factor to be included in asset pricing models. We test also the liquidity factor offered by Pastor Lubois on his web pages. The liquidity factor doesn’t appear to add significantly to any of the five portfolios in these three industries. The time period in all presented estimations is 1975-2011.

In the stepwise model selection process, the reversal factor did not load statistically significantly on manufacturing or healthcare industries. Table 8 presents the four-factor model time series regression results for manufacturing and healthcare industry and five-factor model results for hitec industry for one year. The results for R&D intensive portfolio excess returns after two years were not statistically significant for manufacturing. For hitec and healthcare the persistence for excess returns was tested lasting for five years. However, only one-year results are shown in the Table 8 with results confirming the findings from industry portfolio regressions. In Table 8 the first column shows the R&D to market capitalization portfolio from the lowest to highest R&D intensity and the results for each industry are shown in separate panels.
Table 8. Factor Model Regressions for Monthly Returns (in Percent) on Portfolios Sorted by R&D Relative to Market Equity for Industries

Each year from 1975 to 2011, all stocks are ranked by R&D expenditure relative to market value of equity, and assigned to one of five equally sized portfolios. Stocks with no R&D expenditures are assigned to a separate portfolio. The sample includes all NYSE, AMEX and Nasdaq domestic primary issues with coverage on the CRSP and COMPUSTAT files. Estimated coefficients, t-statistics, adjusted $R^2$, and IR are reported for the four- and five-factor model presented on the equations (6) and (7): The model is estimated using monthly returns from each of the first year following portfolio formation.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>a</th>
<th>t(a)</th>
<th>b</th>
<th>t(b)</th>
<th>s</th>
<th>t(s)</th>
<th>h</th>
<th>t(h)</th>
<th>d</th>
<th>t(d)</th>
<th>r</th>
<th>t(r)</th>
<th>$R^2$</th>
<th>IR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (low)</td>
<td>-0.31</td>
<td>-2.35</td>
<td>1.05</td>
<td>3.449</td>
<td>0.74</td>
<td>1.687</td>
<td>0.31</td>
<td>6.80</td>
<td>-0.23</td>
<td>-7.85</td>
<td>0.82</td>
<td>-0.41</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.10</td>
<td>-0.79</td>
<td>1.04</td>
<td>3.769</td>
<td>0.68</td>
<td>1.711</td>
<td>0.37</td>
<td>8.77</td>
<td>-0.19</td>
<td>-7.36</td>
<td>0.84</td>
<td>-0.14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.33</td>
<td>2.98</td>
<td>0.99</td>
<td>39.17</td>
<td>0.66</td>
<td>18.21</td>
<td>0.33</td>
<td>8.62</td>
<td>-0.11</td>
<td>-4.61</td>
<td>0.85</td>
<td>0.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.37</td>
<td>3.39</td>
<td>1.08</td>
<td>43.02</td>
<td>0.74</td>
<td>20.55</td>
<td>0.40</td>
<td>10.48</td>
<td>-0.15</td>
<td>-6.31</td>
<td>0.87</td>
<td>0.59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 (high)</td>
<td>0.47</td>
<td>2.69</td>
<td>1.06</td>
<td>26.61</td>
<td>1.04</td>
<td>18.19</td>
<td>0.43</td>
<td>7.17</td>
<td>-0.20</td>
<td>-5.30</td>
<td>0.76</td>
<td>0.47</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Hitec

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>a</th>
<th>t(a)</th>
<th>b</th>
<th>t(b)</th>
<th>s</th>
<th>t(s)</th>
<th>h</th>
<th>t(h)</th>
<th>d</th>
<th>t(d)</th>
<th>r</th>
<th>t(r)</th>
<th>$R^2$</th>
<th>IR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (low)</td>
<td>-0.08</td>
<td>-0.43</td>
<td>1.16</td>
<td>27.00</td>
<td>1.16</td>
<td>16.79</td>
<td>-0.77</td>
<td>-10.44</td>
<td>-0.34</td>
<td>-8.27</td>
<td>0.06</td>
<td>0.71</td>
<td>0.83</td>
<td>-0.07</td>
</tr>
<tr>
<td>2</td>
<td>0.50</td>
<td>3.01</td>
<td>1.12</td>
<td>29.49</td>
<td>1.16</td>
<td>18.86</td>
<td>-0.83</td>
<td>-12.61</td>
<td>-0.30</td>
<td>-8.11</td>
<td>0.25</td>
<td>3.36</td>
<td>0.86</td>
<td>0.52</td>
</tr>
<tr>
<td>3</td>
<td>0.48</td>
<td>2.68</td>
<td>1.12</td>
<td>27.53</td>
<td>1.18</td>
<td>18.08</td>
<td>-0.56</td>
<td>-8.05</td>
<td>-0.31</td>
<td>-7.93</td>
<td>0.21</td>
<td>2.58</td>
<td>0.83</td>
<td>0.47</td>
</tr>
<tr>
<td>4</td>
<td>0.98</td>
<td>5.40</td>
<td>1.09</td>
<td>26.38</td>
<td>1.22</td>
<td>18.32</td>
<td>-0.47</td>
<td>-6.63</td>
<td>-0.23</td>
<td>-5.75</td>
<td>0.30</td>
<td>3.61</td>
<td>0.82</td>
<td>0.94</td>
</tr>
<tr>
<td>5 (high)</td>
<td>1.14</td>
<td>4.89</td>
<td>1.05</td>
<td>19.79</td>
<td>1.35</td>
<td>15.72</td>
<td>-0.29</td>
<td>-3.20</td>
<td>-0.21</td>
<td>-4.20</td>
<td>0.29</td>
<td>2.73</td>
<td>0.73</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Panel C: Healthcare

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>a</th>
<th>t(a)</th>
<th>b</th>
<th>t(b)</th>
<th>s</th>
<th>t(s)</th>
<th>h</th>
<th>t(h)</th>
<th>d</th>
<th>t(d)</th>
<th>r</th>
<th>t(r)</th>
<th>$R^2$</th>
<th>IR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (low)</td>
<td>-0.24</td>
<td>-1.31</td>
<td>0.95</td>
<td>22.85</td>
<td>1.01</td>
<td>16.78</td>
<td>-0.23</td>
<td>-3.69</td>
<td>-0.17</td>
<td>-4.34</td>
<td>0.75</td>
<td>-0.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.38</td>
<td>1.91</td>
<td>0.91</td>
<td>20.13</td>
<td>1.10</td>
<td>16.87</td>
<td>-0.33</td>
<td>-4.83</td>
<td>-0.14</td>
<td>-3.25</td>
<td>0.73</td>
<td>0.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.67</td>
<td>3.14</td>
<td>0.92</td>
<td>18.78</td>
<td>1.07</td>
<td>15.15</td>
<td>-0.41</td>
<td>-5.57</td>
<td>-0.13</td>
<td>-2.77</td>
<td>0.70</td>
<td>0.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1.03</td>
<td>3.91</td>
<td>0.89</td>
<td>14.83</td>
<td>1.38</td>
<td>15.92</td>
<td>-0.50</td>
<td>-5.54</td>
<td>-0.11</td>
<td>-1.93</td>
<td>0.66</td>
<td>0.68</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 (high)</td>
<td>1.24</td>
<td>4.32</td>
<td>0.98</td>
<td>14.96</td>
<td>1.53</td>
<td>16.21</td>
<td>-0.31</td>
<td>-3.08</td>
<td>-0.22</td>
<td>-3.59</td>
<td>0.65</td>
<td>0.75</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(Source: compustat/crsp)
Panel A shows 5.64 % yearly excess returns in the first year for the high-intensity portfolio for manufacturing industry. The low-intensity portfolio excess return for manufacturing industry is negative and significant at -3.72 % p.a. This negative return of the low R&D intensity portfolio will contribute to long short investment portfolio returns, which are examined later in Table 10. In Panel B and C, the hitec and healthcare industries’ low-intensity portfolios do not yield statistically significant excess returns.

In Panel B and C, the high-intensity portfolios for hitec and healthcare show higher excess returns than manufacturing. The excess returns are 13.68 % p.a. for hitec and 14.88 % p.a. for healthcare, both statistically significant at 1 % level. This finding suggests that the high returns of the high R&D intensity portfolios shown in Table 5 are dominated by these two industries. The variability of the excess returns is higher for healthcare, resulting in lower information ratios than for the hitec industry. The information ratios for the two highest intensity portfolios in hitec are very good at 0.94 and 0.85, see Grinold & Kahn (1992). Interestingly, the information ratios are the highest for the second highest intensity portfolio 4 in manufacturing and hitec and only in the healthcare the highest intensity portfolio 5 also results in the highest information ratio.

Factor loadings differ between the industries. While the market beta in healthcare industry is lower than 1.0 for all R&D intensity portfolios, it’s generally above 1.0 for manufacturing and hitec. The highest intensity portfolios show high exposure to small stocks for all three industries. The value premium factor has a positive sign in the manufacturing industry and negative in both healthcare and hitec industries. The reversal factor loads statistically significantly only for the hitec industry. Adjusted $R^2$ remain at a high level, although they are lower than in Table 5 without industry breakdown. Especially in the healthcare industry, $R^2$ values are lower than in other industries varying from 0.65 to 0.75. Similar to Table 5 and also to Chan et al. (2001) Table VI, the lowest $R^2$ are found in the highest R&D intensity portfolios. These low $R^2$ imply model fitting problems and possible more severe omitted risk factor problems for these portfolios.
4.3 Investment Strategy Enhancement

We enhance the Chan et al. (2001) investment strategy by concentrating on previously found R&D intensive industries and implementing new sorting criteria. The second sorting criteria tries to mimic previously discussed Porter’s generic competitive strategies by using DuPont equation components as a proxy. The purpose is to improve the R&D intensive investment strategy returns by employing Porter’s competitive strategy sorting.

Table 9 shows the results for R&D intensity and strategy portfolio returns controlled with Fama-French 10 industry portfolios. In Table 9 the first column shows the industry, the second column the strategy and the third column the R&D intensity portfolio. Companies are sorted into two different portfolios within industries by the strategy. The first portfolio contains companies which implement either a cost leadership or product differentiation strategy. The second portfolio contains the rest of the stocks. The no-strategy firms we regard as comparable to what Porter calls stuck in the middle companies. All industry stocks are further ranked by R&D expenditure relative to market value of equity, and assigned to one of five equally sized portfolios.

Table 9. R&D to Market Capitalization Portfolios’ Excess Returns Over Industry Benchmark Portfolios with Strategy Breakdown

Each year from 1975 to 2011, all stocks are divided by the strategy they implement and then their R&D expenditure relative to the equity market value by their industry, and assigned to one of five equally sized portfolios. Stocks with no R&D expenditures are assigned to a separate portfolio. The sample includes all NYSE, AMEX and Nasdaq domestic primary issues with coverage on the CRSP and COMPUSTAT files. Each portfolios average return is shown in excess of the equally weighted return on a control portfolio of stocks matched by Fama-French 10-industry portfolios in the first through third postformation years.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Strategy</th>
<th>R&amp;D-portfolio</th>
<th>First Year</th>
<th>Second Year</th>
<th>Third Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacture</td>
<td>cost or diff</td>
<td>5 (high)</td>
<td>0.068 ***</td>
<td>0.060 ***</td>
<td>0.053 ***</td>
</tr>
<tr>
<td>Manufacture</td>
<td>no-strategy</td>
<td>1 (low)</td>
<td>-0.149 ***</td>
<td>-0.067 **</td>
<td>-0.055 *</td>
</tr>
<tr>
<td>High-tech</td>
<td>cost or diff</td>
<td>5 (high)</td>
<td>0.137 ***</td>
<td>0.099 ***</td>
<td>0.065 ***</td>
</tr>
<tr>
<td>High-tech</td>
<td>no-strategy</td>
<td>1 (low)</td>
<td>-0.173 ***</td>
<td>-0.088 **</td>
<td>-0.021</td>
</tr>
<tr>
<td>Healthcare</td>
<td>cost or diff</td>
<td>5 (high)</td>
<td>0.138 ***</td>
<td>0.083 **</td>
<td>0.045</td>
</tr>
<tr>
<td>Healthcare</td>
<td>no-strategy</td>
<td>1 (low)</td>
<td>-0.196 ***</td>
<td>-0.118 ***</td>
<td>0.044</td>
</tr>
</tbody>
</table>

(Source: crsp / compustat, */***/*** = significance at 5% / 1% / 0.1% level)
Table 9 shows results only for strategy implementing portfolios with high R&D intensity and no-strategy portfolios with low R&D intensity. These are the interesting portfolios when building an investment strategy. Returns are in excess of Fama-French 10 industry portfolios for one to three years after portfolio formation with corresponding t-statistics.

When the Table 9 results are compared to the Table 7, the high R&D intensity strategy portfolios for the manufacturing, hitec and healthcare industry do not show much difference. The low R&D intensity portfolios with no-strategy, however, show lower industry-adjusted returns than pure low R&D intensity industry portfolios. These results are all statistically significant. Manufacturing has -14.9 % compared to -6.4 %, hitec -17.3 % compared to -9.3 % and healthcare -19.6 % compared to -13.7 % in yearly returns under the industry mean. These higher negative returns suggest that strategy proxy can improve the excess returns for the investment strategy zero portfolios by better selecting the stock to be short.

The time series regression showed two- to five-year persistence for the excess returns depending on the industry. The strong persistence is also present in Table 9. Despite the persistence, we focus on the one-year excess returns in the investment strategy. The first reason is economically highest excess returns for the first-year portfolios. Table 4 also shows this clearly when looking at the highest R&D intensive portfolio first-year returns. In Table 4, past losers have high positive returns and past winners high negative returns. The second reason is the potential omitted risk factor problems, which are more severe for longer time intervals.

Table 10 presents the factor model time series regression results for manufacturing, hitec and healthcare industries for three years. In Table 10 the first column shows the industry, the second column the strategy and the third column the R&D expenditures to market capitalization portfolio.
Table 10. Factor Model Regressions for Monthly Returns (in Percent) on Portfolios Classified by Strategy and R&D Relative to Market Equity

Each year from 1975 to 2011, all stocks are divided by the strategy they implement and then ranked by R&D expenditure relative to market value of equity, and assigned to one of five equally sized portfolios. Stocks with no R&D expenditures are assigned to a separate portfolio. The sample includes all NYSE, AMEX and Nasdaq domestic primary issues with coverage on the CRSP and COMPUSTAT files. Estimated coefficients, t-statistics, adjusted R², and IR are reported for the four- and five-factor model presented on the equations (6) and (7): The model is estimated using monthly returns from each of the first year following portfolio formation.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Strategy</th>
<th>R&amp;D-portfolio</th>
<th>a</th>
<th>t(a)</th>
<th>b</th>
<th>t(b)</th>
<th>s</th>
<th>t(s)</th>
<th>h</th>
<th>t(h)</th>
<th>d</th>
<th>t(d)</th>
<th>r</th>
<th>t(r)</th>
<th>R²</th>
<th>IR</th>
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<tr>
<td>Panel A: Industry portfolios divided by strategy and R&amp;D intensity</td>
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</tr>
<tr>
<td>Manufac.</td>
<td>cost or diff</td>
<td>5 (High)</td>
<td>0.62</td>
<td>3.38</td>
<td>1.01</td>
<td>24.37</td>
<td>0.97</td>
<td>16.21</td>
<td>0.42</td>
<td>6.57</td>
<td>-0.18</td>
<td>-4.53</td>
<td>0.73</td>
<td>0.59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufac.</td>
<td>no-strategy</td>
<td>1 (low)</td>
<td>-1.06</td>
<td>-3.80</td>
<td>1.09</td>
<td>17.30</td>
<td>0.92</td>
<td>10.11</td>
<td>0.12</td>
<td>1.27</td>
<td>-0.33</td>
<td>-5.47</td>
<td>0.58</td>
<td>-0.67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hitec</td>
<td>cost or diff</td>
<td>5 (High)</td>
<td>1.25</td>
<td>5.41</td>
<td>1.06</td>
<td>20.04</td>
<td>1.23</td>
<td>14.48</td>
<td>0.24</td>
<td>2.29</td>
<td>-0.16</td>
<td>-3.13</td>
<td>0.24</td>
<td>2.29</td>
<td>0.71</td>
<td>0.95</td>
</tr>
<tr>
<td>Hitec</td>
<td>no-strategy</td>
<td>1 (low)</td>
<td>-0.72</td>
<td>-2.30</td>
<td>1.15</td>
<td>16.16</td>
<td>1.38</td>
<td>12.06</td>
<td>0.09</td>
<td>0.61</td>
<td>-0.38</td>
<td>-5.56</td>
<td>0.09</td>
<td>0.61</td>
<td>0.66</td>
<td>-0.40</td>
</tr>
<tr>
<td>Healthcare</td>
<td>cost or diff</td>
<td>5 (High)</td>
<td>1.59</td>
<td>5.61</td>
<td>0.86</td>
<td>13.32</td>
<td>1.06</td>
<td>11.43</td>
<td>-0.04</td>
<td>-0.46</td>
<td>-0.20</td>
<td>-3.27</td>
<td>0.52</td>
<td>0.98</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthcare</td>
<td>no-strategy</td>
<td>1 (low)</td>
<td>-0.82</td>
<td>-2.42</td>
<td>1.05</td>
<td>13.58</td>
<td>1.19</td>
<td>10.63</td>
<td>-0.17</td>
<td>-1.47</td>
<td>-0.25</td>
<td>-3.45</td>
<td>0.52</td>
<td>-0.42</td>
<td></td>
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<tr>
<td>Panel B: Zero portfolios by industry with and without strategy sorting</td>
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</tr>
<tr>
<td>Manufac.</td>
<td>no</td>
<td>zero</td>
<td>0.78</td>
<td>4.39</td>
<td>0.01</td>
<td>0.26</td>
<td>0.30</td>
<td>5.19</td>
<td>0.12</td>
<td>1.93</td>
<td>0.03</td>
<td>0.68</td>
<td>0.06</td>
<td>0.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufac.</td>
<td>yes</td>
<td>zero</td>
<td>1.67</td>
<td>5.82</td>
<td>-0.08</td>
<td>-1.21</td>
<td>0.05</td>
<td>0.54</td>
<td>0.29</td>
<td>2.95</td>
<td>0.15</td>
<td>2.40</td>
<td>0.03</td>
<td>1.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hitec</td>
<td>no</td>
<td>zero</td>
<td>1.22</td>
<td>5.65</td>
<td>-0.1</td>
<td>-2.11</td>
<td>0.19</td>
<td>2.37</td>
<td>0.48</td>
<td>5.63</td>
<td>0.13</td>
<td>2.67</td>
<td>0.23</td>
<td>2.33</td>
<td>0.16</td>
<td>0.99</td>
</tr>
<tr>
<td>Hitec</td>
<td>yes</td>
<td>zero</td>
<td>1.97</td>
<td>6.24</td>
<td>-0.09</td>
<td>-1.31</td>
<td>0.51</td>
<td>4.09</td>
<td>-0.15</td>
<td>-1.33</td>
<td>0.15</td>
<td>1.07</td>
<td>0.22</td>
<td>3.21</td>
<td>0.10</td>
<td>1.09</td>
</tr>
<tr>
<td>Healthcare</td>
<td>no</td>
<td>zero</td>
<td>1.48</td>
<td>5.38</td>
<td>0.03</td>
<td>0.49</td>
<td>0.53</td>
<td>5.82</td>
<td>-0.07</td>
<td>-0.78</td>
<td>-0.05</td>
<td>-0.88</td>
<td>0.09</td>
<td>0.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthcare</td>
<td>yes</td>
<td>zero</td>
<td>2.41</td>
<td>5.98</td>
<td>-0.19</td>
<td>-2.10</td>
<td>-0.12</td>
<td>-0.94</td>
<td>0.13</td>
<td>0.92</td>
<td>0.05</td>
<td>0.61</td>
<td>0.02</td>
<td>1.05</td>
<td></td>
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</tr>
<tr>
<td>Panel C: Zero portfolio over all industries without strategy sorting</td>
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<td></td>
</tr>
<tr>
<td>All</td>
<td>no</td>
<td>zero</td>
<td>0.99</td>
<td>6.42</td>
<td>-0.07</td>
<td>-2.10</td>
<td>0.24</td>
<td>4.33</td>
<td>0.12</td>
<td>2.06</td>
<td>0.12</td>
<td>3.50</td>
<td>0.33</td>
<td>4.79</td>
<td>0.19</td>
<td>1.12</td>
</tr>
</tbody>
</table>

(Source: compustat/crsp)
In Table 10 Panel A shows the time series regression results for the portfolios defined previously in the Table 9. Companies are sorted into two different portfolios within industries by the strategy. The first portfolio contains companies which implement either a cost leadership or product differentiation strategy. The second portfolio contains the rest of the stocks. All industry stocks are further ranked by R&D expenditure relative to market value of equity, and assigned to one of five equally sized portfolios. Table 10 employs the four- and five-factor regression models described in Equations (6) and (7).

Panel A shows how the strategy division improves the returns of the high R&D intensity portfolios. It also improves the information ratios of these portfolios. The second enhancement is that the strategy division shows higher negative excess returns for low intensity portfolios which are the companies we define to be stuck in the middle. The strategy division especially improves the statistical significance of the low intensity portfolios, which results in higher statistical significance and higher returns for the zero portfolios in Panel B. In a stepwise model selection process the model with the lowest alpha estimate is selected in Panel B.

Table 10 Panel B compares the zero portfolio results, with (yes) and without (no) strategy double sorting. The monthly excess returns without strategy sorts are higher in hitec (1.22 %) and healthcare (1.48 %) than the excess return for the zero portfolio over all industries (0.99 %) shown in Panel C. An investment strategy which takes long position on high R&D intensity strategy stocks and short position on low R&D intensity no-strategy stocks yields higher excess returns than without strategy double sorting in all of the three industries. The monthly excess returns are 1.67 %, 1.97 % and 2.41 % for manufacturing, hitec and healthcare industries. All returns are higher than the zero portfolio excess return (0.99 %) over all industries. Strategy approach also improves the statistical significance and persistence of the excess returns. Persistence was tested for zero portfolios lasting for five years, results not shown.

The model fitting suffers from strategy sorts. The $R^2$ figures are notably lower for the low intensity portfolios. The corresponding $R^2$ for manufacturing, hitec and
healthcare industries are 0.58, 0.66 and 0.52 compared to 0.82, 0.83 and 0.75 without strategy sorts, see Table 8. Also high intensity portfolios’ $R^2$ are lower. This is especially notable in healthcare industry, where $R^2$ drops to 0.52 compared to 0.65 in Table 8. Factor loadings show that there is no more statistical significance for value premium for healthcare industry. Also the low intensity portfolios in manufacturing and hitec lose the value premium’s explanatory power.

The model fitting implies problems from portfolios getting smaller and then more affected by outliers. This concerns especially to low intensity portfolios because our strategy division classifies less than half of the stock as ‘stuck in the middle’ portfolios. When the model fitting is suffering, the role of the unexplained risk increases. Factor contribution shows that exposures tilt towards small stock, which may partly explain the higher volatility of the excess returns. While the excess return can be enhanced a great deal with the use of strategy sorting, the information ratios improve only slightly. Strategy approach therefore partially fails to eliminate unwanted risk and unnecessary volatility to improve the information ratios in the same extent as the excess returns.
5 CONCLUSION

The partial replication of Chan et al. (2001) study found results which are consistent with them. Chan et al. (2001) used data until the year 1995. We use data reaching the year 2011. The overall results are similar to them. The highest R&D intensity portfolio has excess returns over common risk factors. These returns are slightly higher than in Chan et al. (2001). Similar to them, we also find that the highest intensity portfolio excess returns seem to be driven by past losing stocks.

Fama-French 5 x 5 size, adjusted book-to-market control portfolio results show further support for hypothesis H1: R&D intensity (measured by R&D expenses to market value of equity) has explanatory power over stock returns. The excess returns for high intensity portfolios were 6.05 % p.a. and 6.78 % p.a. at 1 % significance level. Control portfolio results with double sorting over past 3-year returns strengthen the evidence for the return reversal nature of the R&D intensive portfolios. Factor model regressions support the results found with control portfolios. The highest R&D intensive portfolios have statistically significant excess returns over three and even five years. These excess returns were higher than in the reference study, being 9.24% p.a. for the first year and 8.28 % p.a. for the second and third year, compared to 6.60 %, 6.24 % and 6.36 % p.a. from the first to third year found by Chan et al. (2001).

With industry control portfolio and time series regression, we found support for our second hypothesis H2: R&D intensity (measured by R&D expenses to market value of equity) has explanatory power over stock returns only among the high R&D intensity industries. The industry time series regressions reveal that the industry-related R&D intensity excess returns do not exist in all ten industries. After controlling for common risk factors, market, size, book-to-market, momentum and reversal, the excess returns are found in three industries. These industries are hitec, healthcare and manufacturing. However, the excess returns for manufacturing are only slightly positive and not persistent, lasting only for one year.
Lastly, similar to Ciftci et al. (2009), we show that company strategy is an important ingredient while building an investment strategy. We use sorting criteria which mimic the Porter competitive strategy the firms are implementing. We suggest that investors can enhance profits by taking into account the competitive strategy choices and implementing industry focused bets. An investment strategy which takes short position on ‘stuck in the middle’ low R&D intensity stocks and long position on competitive strategy implementing high R&D intensity stocks yields higher excess returns than a plain R&D intensive strategy. Specifically the median asset turnover and gross profit seem to separate the stocks that perform poorly over next year among the R&D intensive stocks.

Our study shows that R&D expenses give valuable information to investors, which can be used while building an investment strategy. Investors should take into account the off-balance sheet investment, which the R&D immediate expensing rule generates. R&D investments create high information asymmetry between company owners and company insiders. Because of scarce information, investors should carefully examine the company and the industry where the company operates. Investors should also pay attention to the differences in company strategies and corporate governance practices, especially when companies are involved in high level risky investments such as R&D.

This study adds to a long list of literature by providing evidence for the R&D intensity and stock returns relationship on U.S. stock markets over a thirty year period, 1975-2011. We find support for Chan et al. (2001) results with 16 years more data. R&D intensity measured by R&D expenses to market value of equity seems to have value relevance and predictive power over subsequent stock returns. Similar to Anagnostopoulou & Levis (2008) and Lev et al. (2007), we find this to be a phenomenon in certain R&D intensive industries. However, we do not address the reasons for the excess returns and the returns might just be compensation for the extra risk of the R&D intensity. We leave this question open question for further studies.
The elementary nature of this study leaves many questions open and available for future studies. The fact that the reasons for the excess returns are not clear challenges one to explore the characteristics of these companies in more detail. The most challenging issue is to address the risks attributed to R&D. Despite the extensive amount of research done by academics, this issue remains partly open. The undiscovered issue in our investment strategy is whether the strategy could be implemented on real stock markets due to liquidity concerns.

Advertising creates another form of intangible capital by brand creation. One topic would be to study R&D and advertising jointly. Also, advertising has a different role in different industries and companies use advertising for different purposes. Our data shows that in healthcare industry advertising spending is much greater than on the hitec industry. The excess returns in our study were the highest in healthcare. It would be interesting to study how much (if any) of these excess returns can be explained by advertising expenses. One possibility would be treat advertising as only short lived assets (Bublitz & Ettredge 1989). The current advertising expenses could be studied jointly with R&D expenditures.

The time span of the study is 36 years and thus covers several boom bust cycles. These cycles could be taken into account when studying R&D intensity and its benefits. Another relevant topic with the long time series is the possible structural breaks in the data. Amir et al. (2007), suggest that there is a shift towards more risky R&D strategies. According to Amir et al. (2007), the shift results from information technology breakthroughs on certain R&D intensive industries. They date the shift to the year 1986 and divide their study on to two samples 1972-1985 and 1986-1999. Our study could be extended to study the different time periods more carefully. This could be done with a reasonable amount of effort, since the code developed allows taking the time period as a parameter. Also, possible business cycle correlation on R&D returns would be interesting topic. The correlations could be used with cross industry long short portfolios. In this case the quarterly data of R&D expenses would be more appropriate since GDP data is available quarterly and even monthly.
The R&D expenses calculation with a fixed straight line method also leaves space for further improvement. Studies show that R&D benefits are actually dependent on the industry the company operates in (Lev & Sougiannis 1996; Amir et al. 2007). The useful life of R&D capital in their studies ranged from five to nine years. One simple improvement would be to use these industry specific values of R&D capital and industry-adjusted amortization rates. However, this modification probably has only a slight effect on the results, since over five-year expenses have much less weight on R&D capital calculation than recent year R&D expenses.

The simple proxy for the company strategy leaves room for further development of the investment strategy. Company board is in a key role when selecting and monitoring the strategy to be implemented. Good corporate governance is important to effective strategy implementation. The strategy proxy could be further enhanced by using variables which proxy corporate governance. These variables could be used jointly with DuPont components which we use to define Porter’s generic strategies. Another enhancement could be brought by combining the M&A data similar to Kallunki et al. (2009) to adjust sorting process among R&D intensive industries. This could result in improved sorting criteria of the profitability component and lead to better selection of top performing companies. We leave these ideas for possible further study.
REFERENCES


Center for Research in Security Prices (2001), CRSP Delisting Returns, The University of Chicago Graduate School of Business.


APPENDIX

Appendix 1. Industry SIC codes

1 NoDur Consumer NonDurables -- Food, Tobacco, Textiles, Apparel, Leather, Toys
   0100-0999, 2000-2399, 2700-2749, 2770-2799, 3100-3199, 3940-3989

2 Durbl Consumer Durables -- Cars, TV's, Furniture, Household Appliances
   2500-2519, 2590-2599, 3630-3659, 3710-3711, 3714-3714, 3716-3716, 3750-3751
   3792-3792, 3900-3939, 3990-3999

3 Manuf Manufacturing -- Machinery, Trucks, Planes, Chemicals, Off Furn, Paper, Com Printing
   2520-2589, 2600-2699, 2750-2769, 2800-2829, 2840-2899, 3000-3099, 3200-3569
   3580-3621, 3623-3629, 3700-3709, 3712-3713, 3715-3715, 3717-3749, 3752-3791
   3793-3799, 3860-3899

4 Enrgy Oil, Gas, and Coal Extraction and Products
   1200-1399, 2900-2999

5 HiTec Business Equipment -- Computers, Software, and Electronic Equipment
   3570-3579, 3622-3622, 3660-3699, 3694-3699, 3810-3839, 7370-7372, 7373-7373, 7374-7374
   7375-7375, 7376-7376, 7377-7377, 7378-7378, 7379-7379, 7391-7391, 8730-8734

6 Telem Telephone and Television Transmission
   4800-4899

7 Shops Wholesale, Retail, and Some Services (Laundries, Repair Shops)
   5000-5999, 7200-7299, 7600-7699

8 Hlth Healthcare, Medical Equipment, and Drugs
   2830-2839, 3693-3693, 3840-3859, 8000-8099

9 Utils Utilities
   4900-4949

10 Other Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance