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The effect of R&D on firm values in the Swedish market

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Abstract

In this study, we investigate the economic value of R&D investments for i) all Swedish listed firms, ii) firms of different sizes, iii) manufacturing firms, and iv) high-technology firms. We use the market value approach to proxy the economic value of intangible assets created by R&D activities on the Swedish market over time. Our results show support for the hypothesis that R&D investments provide economic value not accounted for in the balance sheet and that it provides even greater value for manufacturing firms and high-technology firms. Further, we use a three-fold size-category partition and can generally show increased importance of R&D for the market value of larger firms. The paper extends the field of research by applying the market value approach to value intangible assets from R&D investments in the Swedish market. Furthermore, using this approach to estimate the economic value of R&D for high-technology firms in the internet era has, to the best of our knowledge, not been done previously.

Supervisor: Henrik Andersson

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1. Introduction

1.1 Background

Knowledge can be defined as the accumulation of *prior* innovations and serves as a basis for *new* innovations by providing frameworks, or schemata, for new innovations to rely on. Thus, knowledge is the basis on which technology is created. Technology can be defined as the application of scientific knowledge to the practical aims of human life, and it is the key driver of economic growth (Hausmann, Dominguez, 2022). Companies engage in research and development (R&D) activities to harness technological development in pursuit of economic growth (Davila et al., 2007 Chapter 1). Knowledge can be assigned economic value due to its ability to generate economic returns, which makes knowledge adhere to the specifications of an asset in the accounting system. However, in contrast to tangible assets such as inventory or property, plant, and equipment, knowledge is not physical in nature. Intangible assets are those that are not physical in nature, but rather only exist within our minds or in codified form (Kumar, 2015 Chapter 1). Intangible assets can be divided into intangible properties and intangible resources (Hall, 1992). Intangible properties are legally protected knowledge while intangible resources are not.

The 1980s and 1990s saw the developed world transitioning from industrial capitalism to a new economy, where businesses were less focused on tangible assets, and value creation increasingly relied on knowledge, i.e., intangible assets. Daum (2002 Part 1) states that in the U.S manufacturing and mining sectors in 1982, 62% of capital invested was spent on tangible assets. This number gradually decreased to 16% by 1999. The increasing importance of intangible assets to business could be exemplified by the following quote by the former editor and managing director of the Harvard Business Review, Thomas A. Stewart:

"Information and knowledge are the thermonuclear competitive weapons of our time. Knowledge is more valuable and more powerful than natural resources, big factories, or fat bankrolls. In industry after industry, success comes to the companies that have the best information or wield it most effectively – not necessarily the companies with the most muscle."

Within our current accounting systems, firms are described as assets financed by equity and debt on the balance sheet. In the balance sheet, assets are divided into tangible and intangible assets.

Balance sheets do not reflect the knowledge that intangible assets are supposed to represent in a complete, transparent, and comprehensive manner (Rodov, Leliaert, 2002). Intangible assets are seldom recognized and estimates of their fair values are not disclosed (Barth et al., 2002). Nevertheless, in the case of a company acquisition at a price above the book value of net assets, the consolidated statements report an intangible asset item, goodwill. Goodwill represents the intangible assets that merit a price above net assets' book value (Schuster, 2017). Its value corresponds to the disparity between the acquisition price and the reported book value. In the absence of an acquisition, however, our accounting system would not recognize these intangible assets at their approximated fair value. The measuring issues with intangible assets in our accounting systems can be broken down into the fact that accounting principles and practices presume that all business transactions follow traditional laws of economics. Knowledge, as a type of asset, does not follow these rules because of qualities inherent to its nature. When consumed, knowledge increase rather than depreciate in value and the question of ownership regarding knowledge is very complicated, legally limited to intellectual property rights like patents (Rodov, Leliaert, 2002).

A major issue with measuring intangible assets is that of assigning them a quantitative economic value and looking at intellectual property rights does not give a straightforward answer to this question for a study like this one. The different intellectual property classes are impossible to assign general quantitative value to, as the underlying intangible asset's value is seldom the same for two different intellectual properties of the same type. Valuing each individually is only possible when sufficient information is available, and still requires time-consuming diligence for investors. Either way, only parts of intangible asset values can be and are protected through intellectual property rights. The potential of these intangible asset estimates for our study will be discussed further in the Theory & Literature and Method sections. To solve the difficult question of how to estimate intangible asset levels, we suggest an R&D stock measure previously used in studies such as Hall (1993) and Sandner, Block (2011). This measure is constructed from the quantitative data provided by the accounting measures of R&D spending and capitalization, which is frequently reported by public companies on the Swedish stock market.

1.2 Purpose and contribution

As our economy has become increasingly dependent on knowledge and service-based enterprises, intangible assets have become increasingly important. Understanding intangible assets' risk and value-creation potential should be instrumental to firm valuation. Especially so since accounting instruments have not kept pace with this development. Studies on intangible asset values should thus be very relevant to the modern business community. The purpose of our study is to investigate the difference between accounting and real values of intangible assets. To provide more context to our findings, we will also investigate if and how this differs across some different circumstances, namely firm size, manufacturing sector belongingness and the degree of advanced technology. Using the assumption that the market values assets according to their real value enables us to perform such an investigation quantitatively. There have been a lot of predecessors to our paper taking on this subject, but none using the market value approach and our different circumstantial effects on the Swedish stock market.

1.3 Delimitation

Our study's focus is limited to public companies traded on Swedish markets during the period 1998-2017. Using the market value approach, we follow a method pioneered by Zvi Griliches in his 1981 study of using Tobin's Q to explore the value of intangible assets, although we largely rely on the format this approach takes in Connolly, Hirschey (2005) with adjustments of our own. Guidance for adjustments, and our study in general, is provided by how the market value approach to intangible asset valuation is treated in several other papers. A multitude of research papers about R&D have been published with Bronwyn H. Hall as author or co-author, who similarly to Zvi Griliches has made great contributions to and helped pioneer the research field. In our paper, we refer to Hall (1993), Hall, Jaffe, Trajtenberg (2005), Hall, Oriani (2006) and Hall, Thoma, Torrisi (2007). Amongst these, our study has relied particularly much on Hall (1993) and Hall, Thoma, Torrisi (2007). Sandner, Block (2011) is also of great importance to this paper. The main pillars that our theoretical framework rests on are:

1. The market value approach

2. The clean surplus relation, which we use to derive a value-added model, explaining how the market values companies by looking at historical and current accounting data

1.4 Disposition

This thesis is divided into seven main sections for structure purposes, these are denominated by their numerical order and further divided into subdivisions. The main sections begin with section 1, which is the introduction including Background, Purpose and contribution, Delimitation, and this Disposition. Section 2 is the Theory & Literature section. It begins with a discussion of literature and research in the field, moves on to discuss the theoretical framework and finishes with formalizing the research question, stating the hypotheses and regression formula. In section 2, variables are discussed from a qualitative, theoretical point of view. In section 3, Method, these variables are given a further and more quantitative, pragmatic discussion. Section 3 also covers the methodology of the study. Section 4, Data Selection and Compilation, presents the data sample and statistics. Section 5 displays the empirical results and analysis. The 6th section is Discussion, where the results presented in section 5 are discussed. Finally, we conclude the study in section 7 by drawing main conclusions and stating implications. Section 8 covers the references and section 9 the appendices.

2. Theory & Literature

2.1 Literature review & previous research

There is a mass of studies on the complex subject of understanding how the market values intangible assets, both quantitative and qualitative. Commonly, this is put into the wider context of comprehending how the market values innovation as in studies like Greenhalgh, Rogers (2006). Our study is quantitative and focuses purely on intangible assets without making any explicit implications for innovation. However, the inherent connection between innovative capabilities and intangible assets will be as relevant to our study as it is to the investors who value the observed companies. Note that several papers we refer to, in turn, make references to other studies, which we also refer to. These interdependencies within our research subject relate to certain researchers creating bodies of work with heavy influence on the field. We can trace a lot of theory back to the early studies carried out by Griliches and Hall, e.g Griliches (1980 and 1981) and Hall (1993). As

the methods and assumptions have been tested and examined by several independent researchers over the years, the methods and theories have scrutinized and likely improved. For this study, it implies relevant suggestions for amendments that have been implemented prior to our study.

A range of different estimates have previously been employed in different combinations and contexts within academia as proxies for intangible asset values. R&D expenses and capitalization (hereafter synonymous with R&D spending) are reported accounting measures of internally generated intangible asset investments that have been used in previous research by, amongst others, Griliches (1981) and Hall (1993), to investigate how the market values intangible assets. R&D spending is an innovation input and the context of using R&D spending to proxy intangible asset's values is one where an input measure is used to proxy its output. As stated in Hall, Thoma, Torrisi (2007), R&D spending tends to yield its output after long time periods and in quite an unpredictable manner. Hence, there is no constant connection between the investment put into R&D and its actual economic benefits.

R&D spending can be substituted by a buy-externally approach to innovation, i.e., paying other firms for the results of their R&D efforts or through an acquisition of the entire firm (Getz, Robinson, 2003). Buying externally implies paying fair value for the intangible asset and the accounting system will subsequently value it accordingly in the acquirer's balance sheet. The accounting system thus recognizes the market value of the intangible asset at a certain point in time when the buy-externally approach is applied (Schuster, 2017). At the time of acquisition, the book value of the acquired intangible asset and its market value should be aligned in theory. For internal research and development efforts, however, only development expenses can, and under certain circumstances, be capitalized (Robinson et al., 2020 Chapter 8). This discrepancy causes a non-transparent portrayal of the actual intangible asset base.

Within academia, there are two general approaches to investigating the economic benefits of intangible assets: the productivity approach and the market value approach. The productivity approach looks to productivity variables such as profitability or total factor productivity as the dependent variable to be explained by intangible asset estimates to understand their economic benefit to the firm. The market value approach looks at market prices to explain the economic benefit of intangible assets as the market should discount future performance in terms of generated cash flows.

Regarding the productivity approach's usefulness, it is shown in early academia such as Griliches (1980), Gold (1977), and Mansfield (1968), that R&D is important for long-term productivity growth. If a firm is unable to grow in the longer term, it loses its ability to compete in the market. This implies that R&D spending is a valuable source of future cash flow generation. The reasoning should, at the very least, be true when the strong assumptions used for total factor productivity estimation in the above-mentioned papers hold. That is, assuming only two inputs (capital and labour), constant returns to scale and perfect competition. The productivity approach is exposed to the issues with timing and predictability of R&D output (Hall, Thoma, Torrisi, 2007).

The market value approach looks to market prices for explaining the economic benefit of intangible assets. As the market discounts expected future performance, it, the market value approach does not have the same issues with timing and predictability of R&D output as the productivity approach. When discounting future cash flows to value firms, the market forecasts future firm performance (Berk, de Marzo 2020 Chapter 9). The market value approach is thus not exposed to the timing and predictability issues of R&D output to the extent that these forecasts are accurate. If estimated probabilities of future outcomes are precise, then the market value approach, on average, assigns unmeasured intangible assets their true present value. Pointing to the systematic disparity between fair value and reporting of internally generated intangible assets, Barth et al. (2002) finds that companies with higher R&D spending relative to size are subject to more extensive analyst coverage. That study also states that companies with extensive intangible assets and low levels of analyst coverage likely have less informative prices. Analyst coverage implies greater visibility of the value of intangible assets and yield market values more aligned with fair value. There is a cost-benefit tradeoff associated with gathering material for forecasting. Even if unlimited resources were employed for this purpose, perfect accuracy in forecasting is unattainable. In extension, this has effects on the market value approach as inability to accurately predict future performance yield inaccurate valuation for firms. However, potential market imperfections are an inevitable source of error for theories resting on the pillars of the perfect markets assumption.

Previous studies based on the market value approach have looked at the R&D spending on its own as well as combined with other independent variables to proxy the intangible asset values. For example, R&D spending is used in tandem with patents in Griliches (1981) and Hall, Thoma,

Torrisi (2007), with trademarks in Sandner, Block (2011) and with advertising spending in Connolly, Hirschey (2005) and Hall (1993). Throughout these different combinations of R&D spending and other indicators of intangible assets used in the above-mentioned previous studies, there was a lot of variability in the effect on market value found for the patent and trademark classes of intellectual property rights (Sandner, Block, 2011; Hall, Thoma, Torrisi, 2007). The study of Connolly, Hirschey (2005) included advertising spending but did not find uniformly positive valuation effects nor as significant or consistent data on the advertising variable as it did for R&D spending. Also, reporting of advertising spending is highly fragmented across companies on the Swedish stock market.

Further problematizing the use of intellectual property rights to estimate intangible asset base for market valuation, Harhoff et al. (1999) show that only a small amount of all patents create significant value for their owners and that patent value is highly skewed. Flikkema et al. (2019) show similar patterns for trademarks. The study found considerable variability in qualities between different subgroups of European trademarks, divided upon trademark industry scope and degree of similarity with the applicant's existing trademark portfolio. Also, any analysis using intellectual property rights such as patents or trademarks needs to be aware that these are legal instruments. Differences between jurisdictions as well as changes to the legal environment over time cause a risk of variability in the very definition of these assets.

In Connolly, Hirschey (2005), the market value approach is applied to study the value of intangible assets by looking at R&D spending, complemented by dividing the companies into sub-groups based on size and manufacturing versus non-manufacturing firms. Regressions were conducted separately as well as in ensemble for the subsamples to investigate how the valuation effects of R&D may be dependent on size and manufacturing characteristics. Kafouros (2005) applies the productivity approach to study the relationship between R&D and productivity growth in the U.K manufacturing sector and uses the dimensions of size (like Connolly, Hirschey, 2005) as well as a division into high-technology and low-technology firms. In Hirschey's 2003 book, "Tech Stock Valuation: Investor Psychology and Economics", he presents the effects of firm size on the market value of R&D as an area of interest for future research. This is because findings from his previous studies indicated potential economies of scale or other positive firm-size effects on the market value of R&D at the turn of the millennium. In Connolly, Hirschey (2005), US manufacturing

firms were found to have, on average, about eight times the R&D to sales ratio of non-manufacturing firms. This implies sectoral differences for the manufacturing sector relative to the non-manufacturing sectors. In Kafouros (2005), UK high technology manufacturing firms were found to have roughly twice the R&D to sales ratio of their low-technology counterparts. A conclusion to be drawn from that study and others, such as Sandner, Block (2011), that use subdivisions to check for circumstantial effects, is that these effects seem very real and worthy of further investigation.

2.2 Theoretical framework

Due to the arguments presented in the section above, Literature review & previous research, this study is a market value approach study. The market value approach assumes that companies are valued as bundles of assets and that the price of a firm in financial markets is a function of its assets (Hall, Thoma, Torrisi, 2007). In this approach, the market value of a company is seen as a function of how the stock market values its tangible and intangible assets' capabilities as sources of future cash flow generation (Sandner, Block, 2011). Tobin's Q ratio is the relation between the stock market value and the book value of a company. That is, how the stock market values a company's sources of future cash flow in relation to how the accounting system values total assets (book value):

$$\text{Tobin's Q}_{\text{classic definition}} = \frac{\text{Market value}_{Equity} + \text{Market value}_{Liabilities}}{\text{Book value}_{Equity} + \text{Book value}_{Liabilities}} \qquad \text{(eq. 1)}$$

The underlying theory of Tobin's Q is that the long-run equilibrium market value of the assets that compose a firm should be equal to the book value of those assets, if they are properly measured in the firm's accounting. Thus, deviations from this relationship ($Q \neq 1$) imply that the market fails to value the assets accordingly or that intangible asset values are not recorded at fair value. In the first instance, firms are incentivized to increase or decrease investments (Hall, 1993). Because of this feature, the market should not be expected to stay in disequilibrium for long. However, in the second instance, improper recognition of intangible assets' fair value is commonly a long-run market disparity, as discussed previously. This feature of the Tobin's Q ratio has made it widely used in previous research to investigate the value of sources of future cash flows that may not be properly measured in the balance sheet, as is often the case with intangible assets (Hall, 1993).

Tobin's Q typically includes the values of both debt and equity divided by the firm's total assets. This implies that the ratio is independent of capital structure, and hence extra attractive as an unbiased indicator of asset values that are not measured properly in accounting. A simplified version of dividing the market value of equity by the book value of equity is sometimes used for the definition of Tobin's Q:

$$\text{Tobin's Q}_{\text{simplified}} = \frac{\text{Market value}_{Equity}}{\text{Book value}_{Equity}} \qquad \text{(eq. 2)}$$

However, our study is one of performance, irrespective of capital structure, and thus benefits from using another definition of the Tobin's Q measure. A measure with an operational focus will increase the potential for explaining the market value effects of internally generated intangible assets. We define an operations-focused Tobin's Q as enterprise value in relation to the book value of capital employed:

$$\text{Tobin's Q} = \frac{\text{Market value}_{Equity} + \text{Market value}_{Debt} - \text{Market value}_{Cash\ \&\ marketable\ securities}}{\text{Book value}_{Equity} + \text{Book value}_{Liabilities} - \text{Book value}_{Cash\ \&\ marketable\ securities}} = \qquad \text{(eq. 3)}$$

$$\frac{\text{Market value}_{Equity} + \text{Market value}_{Net\ debt}}{\text{Book value}_{Equity} + \text{Book value}_{Net\ debt}} = \frac{\text{Enterprise value}}{\text{Book value}_{Capital\ employed}}$$

The clean surplus relation states that the difference between current book value of equity and the previous period's book value of equity is equal to the net income accrued plus new issuances of equity less dividends issued during the period. We assume that the clean surplus relation holds to create a value-added model (Skogsvik, 1999). In extension, this is made to model our operations-focused Tobin's Q as linearly dependent on future ROCE (see section 3, Method). Since investors cannot know the future ROCE level for certain, they use forecasting to estimate future expected earnings. This forecasting is based on current and historical data available, often from accounting reports (Berk, de Marzo, 2020 Chapter 9). This corresponds with the view of the market value approach which states that the financial markets value companies based on their bundles of assets' ability to generate future cash flows. Understanding the process behind stock valuation is critical to investigate the value of intangible assets under this assumption.

R&D is the primary, widely available quantitative measure of intangible asset investments for publicly traded firms. As discussed in section 2.1, Literature review & previous research, patents and/or trademarks are sometimes used in quantitative research to indicate innovative performance

and intangible asset values (Sandner, Block, 2011; Hall, Thoma, Torrisi, 2007; Griliches, 1981). However, there are studies pointing to highly skewed values for trademarks (Flikkema et al., 2019) and patents (Harhoff et al., 1999). This presents challenges to using these in quantitative research as an independent variable estimating intangible assets. We are not including any patent-based measure in our study. Following a previously established method (Hall, 1993; Sandner, Block, 2011) we use a depreciating stock of R&D spending to represent current intangible assets, i.e., emulating a balance sheet item by using a stock variable. Connolly, Hirschey (2005), on the other hand, makes use of current R&D spending, i.e., emulating all investments incurred as an income statement item with a flow variable. A beneficial feature of using the market value approach with Tobin's Q is that this method is largely not affected by the effects of externally acquired R&D outputs, since these are included at fair value in the balance sheet. Tobin's Q is equal to 1 if all assets are recorded at fair value, in the sense of fair value being market value as suggested by the perfect market assumption.

Like the Connolly, Hirschey (2005) study about R&D's economic returns using the market value approach, we will investigate how dividing our sample into groups based on firm size and belongingness to the manufacturing sector will affect results. We will also expand the research field by investigating how the degree of advanced technology will affect the results, which to the best of our knowledge has not been done in any prior market value approach study. However, it has occurred in at least one productivity approach study (Kafouros, 2005). The specifics on the subsample partitioning and the different qualifications follow in section 3.3, Category subdivision.

2.3 Research question

The primary purpose of this study is to derive an approximation for what is formulated in our research question:

What is the economic value of R&D investments?

We employ an R&D stock measure, described in detail under section 3, Method, to estimate intangible asset values. Creating a stock of investments into internally generated knowledge like this reduces the measure's exposure to the uncertain timing effect on the value of R&D and yearly fluctuations in spending. The R&D stock is normalized by total assets to create an R&D intensity

measure. This estimates the importance of intangible assets in the asset base, which shows to what extent the firm relies on intangible assets in value creation. The normalization puts the R&D stock in relation to a size measure which corresponds well with our Tobin's Q measure being normalized by book value of capital employed and the other explanatory variables also being in relation to size. Sandner, Block (2011) suggest that a stock measure should be normalized by another stock measure, supporting the choice of normalizing R&D stock with total assets. On the other hand, an R&D flow measure would be more suitable for normalization with sales (flow measure) rather than assets.

Using regression to find out the explanatory power and direction of our R&D stock measure for Tobin's Q lets us quantitatively analyze intangible assets' role in valuation. We hypothesize that this class of assets is not fully measured as a source of future cash flows in the accounting practices, i.e., that a greater concentration of intangible assets in the asset base correlates to a larger Tobin's Q. To isolate the valuation effects of R&D investments in the regression, with Tobin's Q as the dependent variable, we include other predictable contributors to the market value of the firm. Sales Growth, Leverage, and Profitability all give investors indications of future company performance and have good availability as they can derived from annually reported numbers (Connolly, Hirschey, 2005). See section 3.3, Variables, for further detail on the regression variables. The regression formula derived reads as follows:

$$Tobin's\ \mathrm{Q} = \alpha + \beta_1 * R\&D\ intensity + \beta_2 * \text{Sales Growth} + \beta_3 * \text{Leverage} \qquad \text{(eq. 4)}$$

$$+\beta_4 * \text{Profitability} + \varepsilon$$

Leverage is expected to be inversely correlated with market value. Sales Growth and Profitability are expected to be positively correlated with market value. Successful R&D investments should increase future, but also current profitability (Connolly, Hirschey, 2005). Including profitability in the regression should make the coefficient of R&D intensity more conservative, to the extent that the causality between current profitability and successful R&D investments is present in R&D intensity's contribution to Tobin's Q. In that case, those valuation effects are captured by the profitability coefficient rather than the R&D intensity coefficient. Similar reasoning should also apply to the growth variable as successful R&D investments should contribute both to current and future growth because innovation should help firms gain market (Blundell, Griffith, van Reenen, 1999). This implies that current sales growth should capture some benefits deriving from our R&D

stock measure. There are hence two variables in our equation which can make R&D stock's effect on Tobin's Q in our regression more conservative than merited by the pure expected effect on future ROCE. As stated above, we hypothesize that intangible assets are not accurately measured in the accounting system as a source of future cash flows and, in extension, that our R&D intensity estimate of intangible asset levels is expected to have a positive effect on Tobin's Q.

In addition to a regression on our entire sample, we also test different groupings within the sample individually, to investigate the effects of firm size, belongingness to the manufacturing sector and technology level. In addition to a regression on our entire sample, we also test different groupings within the sample individually, to investigate the various effects on firms of different sizes, manufacturing firms and the high-technology firms. Following previous studies' findings, such as Connolly, Hirschey (2005) and Kafouros (2005), we hypothesize that i) larger firms, ii) manufacturing firms, and iii) high-technology firms have a greater positive relation between R&D intensity and Tobin's Q.

To conclude, our hypotheses are:

H_1: There is a positive relation between R&D intensity and Tobin's Q

H_2: Larger firms (in terms of enterprise value) imply a greater positive relation between R&D intensity and Tobin's Q

H_3: Manufacturing firms have a greater positive relation between R&D intensity and Tobin's Q than non-manufacturing firms

H_4: High-technology firms have a greater positive relation between R&D intensity and Tobin's Q than low-technology firms

3. Method

3.1 Research design

To investigate our research question, a quantitative approach is used. The study consists of an investigation of the market value of R&D for listed Swedish firms, dividing the sample based on all observations, manufacturing versus non-manufacturing firms, and high-technology versus low-

technology firms. A firm-size dimension is investigated for the observations as well, as they are partitioned into a three-fold size division of smallest, central, and largest thirds of firms based on enterprise values. The methodologies for the tests are described in the following sections. The research design for our tests is largely consistent with Connolly, Hirschey (2005). These tests have, to the best of our knowledge, not been performed on the Swedish markets in prior studies.

3.2 Value-added model

Under the assumption that the clean surplus relation holds, we can model the market value of equity according to the RIV model (Ohlson, 1995):

$$MV_t^{Eq} = \sum_{t=1}^{T} \frac{BV_{t-1}^{Eq}(ROE_t - r_e)}{(1+r_e)^t} + \frac{BV_t^{Eq}(ROE_{SS} - r_e) / (r_e - g_{SS})}{(1+r_e)^T} \qquad \text{(eq. 5)}$$

Enterprise value is the market value of capital employed, which in turn is the value of equity and net debt, i.e., the capital which a firm pays rents for to use in value creation. Similarly to the RIV model, the value added model can be used to model enterprise value under the assumption of clean surplus accounting (Skogsvik, 1999):

$$EV_t^{total} = MV_t^{Eq} + MV_t^{ND} = \sum_{t=1}^{T} \frac{BV_{t-1}^{CE}(ROCE_t - WACC)}{(1+WACC)^t} + \frac{BV_t^{CE}(ROCE_{SS} - WACC) / (WACC - g_{SS})}{(1+WACC)^T} \qquad \text{(eq. 6)}$$

Treating the future as one period (future) to get a simple insight into what (rough) future variables define current value:

$$EV_{current} = BV_{current}^{CE} + \frac{BV_{current}^{CE}(ROCE_{future} - WACC)}{(1+WACC)} \qquad \text{(eq. 7)}$$

We define an operations-focused Tobin's Q as enterprise value in relation to book value of capital employed:

$$Tobin's\ Q_t = \frac{EV_t}{BV_t^{CE}} \qquad \text{(eq. 8)}$$

Our Tobin's Q measure is redefined as a dependent variable of future ROCE:

$$Tobin's\ Q = \frac{EV}{BV^{CE}} = 1 + \frac{ROCE_{future} - WACC}{(1+WACC)} \qquad \text{(eq. 9)}$$

Assuming a constant weighted average cost of capital. The value-added model can now be rewritten as a simple linear function explaining Tobin's Q with future ROCE:

$$Tobin's\ Q = \alpha + \beta * ROCE_{future} + \varepsilon \qquad \text{(eq. 10)}$$

Since investors cannot know the future ROCE level for certain, they use forecasting to estimate future earnings. Forecasting is based on current and historical data available to analysts (Berk, de Marzo, 2020 Chapter 9). We break down the future ROCE variable into a set of variables commonly used for this type of forecasting. This allows us to isolate the effects of R&D stock to a certain extent:

$$Tobin's\ \mathrm{Q} = \alpha + \beta_1 * R\&D\ intensity + \beta_2 * \text{Sales Growth} + \beta_3 * \text{Leverage} \qquad \text{(eq. 4)}$$

$$+\beta_4 * \text{Profitability} + \varepsilon$$

3.3 Variables

This approach combines operational metrics with their valuation in financial markets and has frequently been applied to assess expected returns of innovation and the value of intangible assets. In this study, we use Tobin's Q as the dependent variable (explained above), defined as:

$$Tobin's\ Q_t = \frac{EV_t}{BV_t^{CE}} \qquad \text{(eq. 8)}$$

Enterprise values as of the reporting dates have been gathered from Factset while assets and cash and short-term investments have been collected from the Compustat database. Note that the use of the selected metrics makes our study un-affected by the capital structure of each company observed.

For the first independent variable, R&D intensity, data is collected from Compustat. The R&D data includes all expenditures (expenses and capitalized R&D) incurred during the year that relate to the development of new product lines and methods of production or services. For the regression, we use a stock variable (as opposed to a flow variable). This is because previously incurred R&D activities add to the knowledge base of a company and that a certain year's R&D spend may not provide any meaningful value for that specific year due to yearly fluctuations and long time-horizons of R&D projects. Using a stock variable of R&D is consistent with the method in Hall

(1993) and Sandner, Block (2011), but inconsistent with Greenhalgh, Rogers (2006) or Connolly, Hirschey (2005) that instead uses a flow variable for R&D. When creating a stock of R&D spending, it should also depreciate over time to reflect how its value decreases over time. In line with previous research, a depreciation rate of 15% (denoted δ) was used to reflect the obsolescence of R&D investments (Sandner, Block 2011; Hall and Oriani, 2006; Hall, Jaffe, Trajtenberg, 2005; Hall, Thoma, Torrisi, 2007):

$$R\&D_t^{stock} = R\&D_t^{flow} + (1-\delta)R\&D_{t-1}^{stock} \qquad \text{(eq. 11)}$$

To compute the initial R&D stock at the first available observation, equation 12 was used. The equation assumes that R&D has been growing at a constant rate, *g*, of 8%, in line with previous research (Sandner, Block, 2011; Hall, Oriani, 2006; Hall et al.., 2007):

$$R\&D_t^{stock} = \frac{1}{\delta+g} R\&D_t^{flow} \qquad \text{(eq. 12)}$$

The availability of R&D expenditures varies between firms and years. According to chapter 6, §1 of the Swedish Annual Accounts Act ("Årsredovisningslagen"), larger companies must provide information on the company's activities in R&D, should it be conducted to more than a small extent. For a group of companies in our sample, only fragmented R&D data has been displayed, making it difficult to establish a reliable R&D stock. These companies have been left out in our research study. This approach has been legitimized by Sandner, Block (2009), who found no such bias in their study. A somewhat larger sample could potentially have been observed by using a shorter time-period as the R&D reporting is fragmented for many companies. However, using a longer period (1998-2017), enables us to look at market valuations through-the-cycle. This implies that we reduce the risk of observing a particularly biased business cycle period. Rather, our dataset captures both recessions and economic booms in the Swedish and the global economies. Finally, the R&D stock is normalized by total assets:

$$R\&D\ intensity_t = \frac{R\&D_t^{stock}}{Total\ Assets_t} \qquad \text{(eq. 13)}$$

For the other independent variables, Sales Growth, Profitability and Leverage, the following definitions are used:

$$Sales\ Growth_t = \left(\frac{Sales_{t=3}}{Sales_{t=0}}\right)^{\frac{1}{3}} - 1 \qquad \text{(eq. 14)}$$

$$Profitability_t = ROCE_t = \frac{EBIT_t}{Capital\ employed_t} \qquad \text{(eq. 15)}$$

$$Leverage_t = \frac{Total\ Debt_t}{Total\ Assets_t} \qquad \text{(eq. 16)}$$

Sales Growth and Leverage correspond to variables used in Connolly, Hirschey (2005). However, we rely on ROCE rather than profit margin. Instead of using a R&D spending to sales ratio, we use a R&D stock normalized by total assets which is in line with Hall (1993) and Sandner, Block (2011). We name the R&D variable in accordance with Sandner, Block (2011) "R&D intensity". This is not to be confused with the use of the same term in Connolly, Hirschey (2005), which instead refers to a flow measure of R&D spending to sales ratio when using the R&D intensity term.

For each of the variables, Compustat has been used to collect data. The period used in this paper concern 1998-2017 and to compute the Sales Growth variable for the first observation, sales data from 1995 has been collected. The need for historical data to compute Sales Growth implies that all companies that have been listed for a shorter period than four years cannot be used in the regression and that we can only start including data for firms from the point in time when they been listed for three years.

3.4 Category subdivision

The first subdivision is between manufacturing and non-manufacturing firms. This is similar to Connolly, Hirschey (2005) that looked at a global sample of firms and used the 2-digit SIC classification of 20-39 as their manufacturing sample. We have instead utilized Factset's sector classification. The manufacturing sample includes the sectors "consumer durables", "consumer non-durables", "producer manufacturing" and "process industries". All other sector belongings are classified as non-manufacturing for this test.

The second subdivision is between high- and low-technology firms. To the best of our knowledge, there are no prior studies on the high- and low-technology segments utilizing the market value

approach. However, Kafouros (2005) have used the sub-group for their study utilizing the productivity approach. Also worth noting is that Kafouros (2005) uses a broader high-technology classification, however, the exact classification method is not disclosed. We have a narrower definition and focus on "electronic technology" and "technology services" which is also the sectors from Factset's sector classification that we include. Bear in mind that Kafouros (2005) look at firm-level data for the years 1989-2002 which implies that the technology-sector, as we know it today, was not as developed and that internet companies were only just emerging.

The third subdivision is between the size of the firm at the time of observation. This is similar to Connolly, Hirschey (2005) and Kafouros (2005). Kafouros uses a two-fold division of small and large firms, while Connolly, Hirschey divides the group into three size-categories (largest, central and smallest third). We follow the Connolly, Hirschey method, and have for each year divided the companies in three groups based on observed enterprise value for each year. The cut-off points for each year's size sub-categories are shown in section 4, Data collection & compilation.

3.5 Regression analysis

To observe the difference in market value based on R&D stock, we conduct a pooled ordinary least squares (OLS) regression with Driscoll-Kraay standard errors using Stata, with Tobin's Q as the dependent variable explained by four independent variables:

$$Tobin's\ \mathrm{Q} = \alpha + \beta_1 * R\&D\ intensity + \beta_2 * \text{Sales Growth} + \beta_3 * \text{Leverage} \qquad \text{(eq. 4)}$$

$$+\beta_4 * \text{Profitability} + \varepsilon$$

We run this regression firstly on all 1,872 observations. Additionally, we divide the companies into three categories to observe the difference within each of these group. We are using criteria described in section 3.3, Category subdivision, to sort the firm observations into manufacturing and non-manufacturing, high- and low-technology and three size-categories. We also perform the regression on each of the size-categories within each category to further observe the value of each of the sub-categories.

4. Data Collection & Compilation

We have collected data on Swedish companies during the time they have been listed for the years 1995-2017. The primary source of data is Compustat and Factset. Sales, R&D spending, EBIT, debt, cash and marketable securities and total assets are collected as per 31 Dec of respective year from Compustat. Enterprise values for the matching dates have been collected from Factset.

Compustat recognized 1,056 firms listed sometime during the period. We have then sorted out companies listed shorter than the four years needed to calculate the Sales Growth variable (three-year compound annual growth rate used). Further, we deducted all companies with incomplete or fragmented R&D data. Lastly, for 14 observations, Factset failed to recognize the enterprise value for the date requested. See the following table for details on the deviation from our original sample to the final sample of 233 companies:

Table 1. Firm observations

Original sample of firms	1,056
Less: listed for a period shorter than four years	-225
Less: incomplete or fragmented R&D data	-584
Less: EV missing on Factset	-14
Final sample of firms	233

Note: the table shows the sample selection procedure

Due to the irregularity of listing during the period, fragmentation in data, and some missing values, it is not the same companies that have been observed for each year. Table 2 displays the number of valid observations of each year during the period:

Table 2. Number of observations per year

Data year	Frequency	% of total	Cumulative
1998	25	1.3%	1.34
1999	38	2.0%	3.37
2000	53	2.8%	6.20
2001	61	3.3%	9.46
2002	74	4.0%	13.41
2003	84	4.5%	17.90
2004	91	4.9%	22.76
2005	96	5.1%	27.88
2006	94	5.0%	32.91
2007	102	5.4%	38.35
2008	107	5.7%	44.07
2009	113	6.0%	50.11
2010	116	6.2%	56.30
2011	118	6.3%	62.61
2012	110	5.9%	68.48
2013	105	5.6%	74.09
2014	107	5.7%	79.81
2015	114	6.1%	85.90
2016	126	6.7%	92.63
2017	138	7.4%	100.00
Total	1,872	100.0%	

Note: the table shows the number observations for each observed year, the % of total and the cumulative distribution of observations over the period

The observational data values increase over time. This is likely due to more companies being listed over time. Also, it might relate to more extensive reporting of R&D data and greater availability of enterprise value for more recently listed firms.

The size comparison rests on the pillars of Connolly, Hirschey (2005) which has been explained previously. The cut-off enterprise values for each year follow in table 3. Note that the column values in table 3 mark the highest and lowest observable value in SEK million that belongs to the group during that year. The central third size category includes values in between the two:

Table 3. Cut-off sizes for various size-categories

Data year	Large (≥)	Small (≤)
1998	32,134	7,993
1999	22,689	2,684
2000	6,532	615
2001	4,338	376
2002	2,058	198
2003	2,498	321
2004	3,193	439
2005	4,220	648
2006	5,391	796
2007	3,755	556
2008	2,275	364
2009	3,227	474
2010	4,955	388
2011	1,886	312
2012	2,907	378
2013	4,165	487
2014	5,076	541
2015	6,518	911
2016	6,267	974
2017	6,114	771
Average	6,510	1,011

Note: the table shows the cut-off enterprise values for each individual year for each size-category

The considerably higher cut-off values in 1998-1999 and 2005-2006 can likely be explained by generally higher valuations on the stock market as well as fewer observations for the first years. Regarding market valuations, the inverse is true for periods such as 2002-2003 and 2011-2012. A fixed cut-off value for all years would also skew the result as there's great variation in the stock market value. The relative size-categories for each year could thus benefit our analysis.

5. Empirics & Analysis

5.1 Descriptive statistics

Table 4. Median of observed values for the different subsamples

	Annual median						
Category	# of obs.	Tobin's Q	R&D intensity	Sales Growth	Leverage	ROCE	EV
Manufacturing	648	1.25	9.3%	5.6%	56.3%	9.3%	6,415
Non-manuf.	1,224	1.29	41.7%	8.7%	42.6%	3.3%	696
High-tech	599	1.22	53.6%	8.8%	48.7%	3.5%	556
Low-tech	1,273	1.29	12.7%	6.6%	50.1%	7.1%	2,595
Largest third	624	1.32	9.4%	6.2%	57.4%	9.4%	29,500
Central third	624	1.31	24.6%	8.8%	46.0%	7.0%	1,263
Smallest third	624	1.18	46.8%	7.1%	35.5%	-9.6%	186
Full sample	1,872	1.28	19.7%	7.2%	49.8%	6.1%	1,306

Note: the table presents descriptive median statistics for each variable for our main sub-categories

5.2 Linear regression assumptions

Firstly, we investigate the correlation between the variables used in the regressions by performing a Pearson Correlation test. The correlation coefficients can take on values ranging from -1 to 1. The first implies a perfect negative correlation while the latter implies a perfect positive correlation. Should the value be 0, there is complete absence of correlation.

Table 5. Pearson correlation test on independent variables

VARIABLES	(1)	(2)	(3)	(4)
(1) R&D intensity	1.0000			
(2) Sales Growth	-0.1350***	1.0000		
(3) Leverage	-0.1710***	-0.0193	1.0000	
(4) Profitability	-0.5743***	0.0877***	0.0883***	1.0000

**** Significant at the 0.01 level, ** Significant at the 0.05 level, * Significant at the 0.10 level*
Note: the table presents correlations between the independent variables and their level of significance

Grewal et al. (2004), states that a value exceeding 0.80 indicates issues regarding multicollinearity. Our correlation matrix shows no strong correlation (>0.8) between any two variables, implying that they should all be relevant independently within our regression and which is why we deem

the correlation between the variables to not have a meaningful distortion to our results. To be noted, however, is the moderate correlation between R&D intensity and Profitability of -0.5743, significant at the 0.01 level. The result was somewhat surprising and will be discussed in section 6, Discussion. Further, we test for multicollinearity through the Variance Inflation Factor (VIF) test. The result shows a mean of 1.27 for our independent variables. According to Johnston et al. (2018), a result exceeding 2.5 is indicative of considerable collinearity. Our results thus show no considerable collinearity and no difficulty in separating the independent contributions of variables. The VIF test is found in Appendix B.

As per the theory discussion (specifically section 2.3, Research question), successful R&D investments were expected to be correlated with current profitability. However, while the findings in table 5 do show a moderate correlation for R&D intensity and Profitability, that correlation is negative. The conclusion of our theory discussion was to expect the existence of an indirect positive valuation effect from R&D intensity stemming from successful R&D investments increasing current profitability. This effect would be assigned the profitability variable in the regression and thus the regression would show a conservative coefficient for R&D intensity's valuation effect. Given the results presented here, we should now instead expect the opposite. R&D stock has a large component that is yearly flow which affects ROCE negatively as larger R&D costs in the income statement decrease EBIT and capitalizations increase capital employed. The theory discussion states that only successful R&D investments should increase current profitability and that R&D projects can have quite varying outcomes. These factors can explain the negative correlation results.

Linear regression is not only dependent on assuming no or little multicollinearity, but also homoskedasticity and no autocorrelation. Assuming normal distribution of residuals is also necessary if confidence intervals or hypothesis testing of regression coefficients is to be performed. We plotted residual errors to look for potential indications of heteroskedasticity. A Breusch-Pagan test was conducted on the residuals to test for potential heteroskedasticity. The test showed indications of heteroskedasticity in our sample. We also performed the Wooldridge test for autocorrelation and were able to reject the null hypothesis that there was no autocorrelation at the 0.05 significance level. To account for these two issues, we use the Driscoll-Kraay robust

estimation method for our regression, following Hoechle (2007). See Appendix A for the Driscoll-Kraay robust standard errors.

To test the normality of residuals, the Jarque-Bera skewness and kurtosis test for normality was performed in Stata. We were able to reject the null hypothesis of normal distribution for the residuals at the 0.01 significance level and conclude that normality of residuals is absent in our regression, making confidence intervals and hypothesis testing of the regression coefficients less reliable.

5.3 Regression analyses

Table 6. Regressions

FIRM SIZE AND CATEGORY	Intercept	R&D intensity	Sales Growth	Leverage	Profitability	R-squared	F	Sample size
All observations								
Small	1.679***	0.535**	0.119	-0.824*	-0.167	0.070	3.5	624
Mid	3.077***	1.324***	0.575**	-3.442***	1.453	0.188	10.5	624
Large	1.877***	4.169***	1.632*	-2.236***	4.409***	0.352	31.2	624
All sizes	2.298***	1.062***	0.348**	-1.660***	1.434***	0.110	10.0	1,872
Manufacturing firms								
Small	1.072**	5.677***	1.970***	-1.575***	3.545***	0.679	29.9	102
Mid	2.381***	5.155*	4.621**	-3.523**	-2.562	0.402	9.7	197
Large	0.589**	-0.578	0.649	-0.338	10.951***	0.614	43.1	349
All sizes	0.846***	5.408***	2.457***	-0.879***	3.923***	0.422	24.3	648
Non-manufacturing firms								
Small	1.385***	0.409*	0.071	-0.360	-0.568	0.069	2.2	526
Mid	3.257***	1.155***	0.486**	-3.305***	1.549	0.146	11.1	424
Large	3.083**	4.341***	1.538	-4.430**	2.254	0.375	146.2	274
All sizes	2.353***	0.978***	0.292*	-1.623**	1.594**	0.090	10.1	1,224
High-technology firms								
Small	0.714*	0.903***	0.211	0.369	0.570	0.207	2.8	273
Mid	1.486*	2.113***	2.379**	-1.398	3.430**	0.199	8.8	239
Large	11.871*	3.116	2.592***	-17.100*	-6.750	0.359	71.8	87
All sizes	1.590***	1.494***	1.232*	-0.733	3.437***	0.145	8.5	599
Low-technology firms								
Small	2.262***	0.098	0.104	-1.544***	-0.970*	0.055	5.9	355
Mid	3.451***	1.100***	0.460**	-4.142***	0.564	0.220	19.4	382
Large	0.901	4.566***	-0.123	-1.253	9.228***	0.512	56.9	536
All sizes	2.484***	0.773***	0.241**	-1.875***	0.555	0.109	13.0	1,273

**** Significant at the 0.01 level, ** Significant at the 0.05 level, * Significant at the 0.10 level*

Note: this table shows the regression coefficients (columns 2-6), R-squared (7), F value (8), and Sample size (9) for the data sample divided into sub-categories and displayed according to relative size within each year

5.3.1 General remarks

Although we did reject, at the 0.05 significance level, that residuals follow a normal distribution, we make a hypothesis test of the null hypothesis that all regression coefficients are equal to zero at the 0.05 significance level. This provides us with the decision rule to reject the null hypotheses for those regressions where F observed in Table 6 is higher than ~2.4. This gives reason to question the regression of small non-manufacturing firms (F=2.2) and also to potentially question the regressions of all small firms (F=3.5), and small high-technology firms (F=2.8) as these would be below or very close to the decision rule threshold if the significance level was changed to the 0.01 level (F~3.5). Due to the size cutoff values for 1998 and 1999, found in Table 3, being considerably higher than for the rest of the sample, regressions were also performed for the period 2000-2017. The findings from these regressions show no indication of impactful distortions to the results presented.

The R&D intensity coefficient is significant at the 0.01 level for all categories when looking at all sizes, however, not for all individual size groups. The importance of dividing the firms into categories to find instances with greater explanatory value is evident and indicating of potential sectoral differences that impair the explanatory value in regressions that combine different sectors. 0.352 is the highest R-squared found amongst subsamples within the All observations category. Exemplifying the potential for better fits when looking at sectoral categories, a higher R-squared than 0.352 is found for all categories within the manufacturing sector, peaking at 0.679 for the small size subsample within the manufacturing category.

5.3.2 All observations

In regressions under the category All observations, we test our hypotheses (H_1 and H_2), that an increase in R&D intensity would lead to a higher Tobin's Q (H_1) and that larger firms have a greater such relation (H_2). The sample yields a positive coefficient for R&D intensity on the All observations category as well as for all subsamples of size within this category. The results also show a greater importance of R&D stock in larger firms in general. This is shown by a higher coefficient as well as a higher R-squared as size increases.

The model provides limited explanatory value for this category as well as all for all subsamples of size within this category. Observing all sizes, R-squared takes on a value of 0.110. Within the

category, the model has least explanatory value for the small size subsamples, with a R-squared of 0.07. Several variables show less significant results when performing the regression on this subsample and the regression was also flagged by our F-test as potentially lacking explanatory value of coefficients. It seems like the regression is not a great fit for the smallest third subsample of All observations. The highest explanatory value in this category is for the largest third of firms (R^2=0.352). The central third size-category falls in between with a R-squared of 0.188. Considering the vast number of factors that can cause variability in market prices without doing the same for our independent variables, and that we only use four independent variables to explain Tobin's Q, the achieved level of R-squared is not deemed unreasonable.

Positive coefficient values for R&D intensity, Sales Growth and Profitability were expected, and the result are in line with this, with one exception being a negative coefficient for Profitability within the smallest third sample group. Leverage was expected to have a negative return as it implies unfavored risk, which is true for all sample size-categories. The profitability coefficient for small and mid-size firms was not significant at the 0.1 level, the same is true for sales growth in small firms.

5.3.3 Manufacturing and non-manufacturing firms

Under section 2.3, Research question, we also hypothesized that the value of R&D should be higher for manufacturing firms as opposed to non-manufacturing firms (H_3). The R&D coefficient displays a significantly higher value for manufacturing firms than for non-manufacturing firms in general and across all the size-divisions but the largest third. Looking at small, and all sizes, we have positive coefficients (5.677 and 5.408) significant at the 0.01 level for the R&D variable. For the central third size segment, we have a positive coefficient as well (5.155), however it is only significant at the 0.1 level. The coefficient for the large segment (-0.578) is ambiguous, being negative and not significant at even the 10% level.

It is found that for the manufacturing firms, the model holds a greater explanatory value than for the whole sample group. The highest R-squared is for the smallest third among manufacturing firms, at 0.679. For all manufacturing firms, we find significant results at the 0.01 level as to all

independent variables and an R-squared at 0.422 which is significantly higher than for the whole sample group.

The non-manufacturing firms show a lower R&D coefficient (0.978) than the manufacturing firms (5.404), but largely in line with the whole sample group (1.062). The hypothesis regarding firm-size (H_2) holds truer, however, as the R&D coefficient increases for each size-category. However, we did flag for the regression coefficients for small non-manufacturing firms potentially lacking explanatory value with a very low F-value and the R-squared value for this segment is very low as well (0.069). This suggests a poor fit within the small segment for our regression model. The largest third of non-manufacturing firms have a high coefficient for the R&D variable of 4.341. The non-manufacturing sample also show less explanatory value for all size-categories and more irregularity as to the significance level. A comparison between the non-manufacturing and manufacturing firms indicates higher explanatory value as well as greater importance of R&D intensity for the market value of manufacturing firms.

5.3.4 High- & low-technology firms

Hypothesis H_4 states that the value of R&D should be higher for high-technology firms as compared to low-technology firms. For high-technology firms of all sizes, containing 599 observations, we find a positive R&D intensity coefficient of 1.494, significant at the 0.01 level. The model has an R-squared of 0.145, when observing high-technology firms of all sizes. The only independent variable that does not show significance is the Leverage variable. Regarding the high-technology small firm size segment, we observe a very low F statistic (F=2.8), raising question regarding the regression model's explanatory value for this category's small segment. The R-squared value for the regression on this segment however is not as bad as with the other segments flagged by the F-test (0.207).

For the high-technology category in general, it seems that an increase in size corresponds with a higher R&D intensity coefficient as well as R-squared value. The highest R&D variable coefficient and R-squared are found for the largest third of high-technology firms

Regarding the low-technology firms, our regression on all size categories has less explanatory value than for the high-technology segment. For all sizes within this category, we do have a

positive R&D variable coefficient of 0.773, however, it is considerably lower than for the high-technology firms (1.494). We observe that the greater valuation effects for high technology versus low-technology firms only seems to be the case for the small and central size categories, and that the opposite holds for the large category. Large low-technology firms display one of the highest R&D intensity coefficients (4.566) in our study, significant at the 0.01 level and with a relatively high R-squared of 0.512.

6. Discussion

6.1 General findings

By reviewing the results from the whole sample group, we can, in line with previous research within the field, report an overall positive effect on the market value of R&D intensity for companies listed on the Swedish market during 1998-2017. Hypothesis H_1 has thus been shown to be true for our sample. Results also indicate support for hypothesis H_2, stating that larger firms should receive a greater benefit of R&D spending. In line with hypotheses H_3 and H_4, R&D is shown to have overall greater effects on market value for manufacturing versus non-manufacturing firms and high-technology versus low-technology firms, respectively. H_3, considering manufacturing firms, has been shown previously in e.g., Connolly, Hirschey (2005). H_4, considering high-technology firms, is a hypothesis we have developed ourselves, based partly on the expected higher productivity of high-technology firms shown in the productivity study of Kafouros (2005). Regarding size effects, we find support for increased importance of R&D intensity for each incrementally larger size-category, in terms of enterprise value, when reviewing our entire sample group. In clear terms, the results show important variations in the effectiveness of R&D spending. It shows that a higher concentration of R&D intensity adds considerably more to firm value for i) larger firms, ii) manufacturing firms (versus non-manufacturing firms), and iii) high-technology firms (versus low-technology firms). As we find explanatory value of Tobin's Q from R&D spending over a long time series, we can conclude that R&D is related to unmeasured source of expected benefits for Swedish firms.

To derive our model, we had to rely on certain assumptions. The main ones included that of the market value approach, that the market values assets to their inherent value, and clean surplus accounting. The assumptions enabled us to use Tobin's Q to find the true inherent value of firms,

viewed as bundles of assets, and to derive a value-added model that allowed for the breakdown of valuation into four independent variables. These were based on current and historical accounting data, and one of them was our estimate of intangible asset levels, R&D intensity. This allowed us to isolate the effects of R&D intensity on Tobin's Q. However, and as is the case with models of human behavior in general, these assumptions are a simplification of a complex reality, and our model is indeed such a simplification.

We came across evidence questioning our assumptions in the theory and the results. For example, the ability of markets to value firms at their inherent value and especially the intangible asset component of that value can be questioned. At the very least, it is fair to say that the practical reality is that markets are not completely accurate in valuations. The market value approach shows values of intangible assets as accurately as the accuracy of the forecasts that the market value of a firm is based on. Our estimate of intangible asset levels is, as discussed in the Theory & Literature section, far from perfect and that is also a major reason why we choose to formulate our research question as "what is the economic value of R&D investments?" rather than intangible assets explicitly. Our results being ambiguous and insignificant for some size-divisions within the categories also point to a more complex reality than described by our model. We also need to keep in mind that our study is based on data from Factset and Compustat. Thus, our study is exposed to potential errors in that data as well as in how the data is structured and interpreted. An example includes Factset's sector classifications, as our analysis of different firm characteristics is based on these sub-groups. As stated in Method, there might also be a bias regarding which companies report R&D spending affecting our sample. However, Sandner, Block (2009) found no evidence of any selection bias. This bias, if present, could potentially skew our sample towards firms where R&D spending is more important which would inflate our findings towards overexaggerating observed trends of importance of R&D intensity to valuation.

6.2 Firm size

Hypothesis H_2 states that larger firms should receive greater benefits of R&D spending. Our results demonstrate support for this hypothesis, in line with previous studies of e.g., Connolly, Hirschey (2005). The exact source of different valuation effects remains unknown. Connolly, Hirschey (2005) discuss that large firms may enjoy scale economies in production and/or marketing of

R&D-intensive goods, geographic scope, or have superior financial resources at their disposal. Schumpeter (1950) state that larger firms are able to innovate more and hence improve their productivity, which, as discussed previously, should also be important for firm value. However, Kafouros (2005) show that economies of scale in terms of productivity exist but tend to disappear as the scale increases. Furthermore, several papers show only a small difference between the importance of R&D for productivity growth between large and small firms (Kafouros, 2005; Link, 1981; Lichtenberg and Siegel, 1991). One could argue that a two-fold division in large and small firms, such as in the Kafouros (2005) study, will likely be more homogenous than a three-fold split like what we have applied in accordance with the method of Connolly, Hirschey (2005). We thus argue that the size-related results in our thesis and Connolly, Hirschey (2005) show a more trustworthy picture of reality as our size-categories of small, central and large companies capture the size-effects to a greater extent. If the distribution of firm sizes is such that it is weighted around the center, a large body of companies that are much alike in size and other characteristics will end up in different groups, using just two size categories. In the three-fold partition, we can more clearly observe the characteristic differences and ensure that firms in the large and small segment indeed differ in size.

Naturally, the connection between firm size and the value of R&D is complex and may stem from numerous causes. Other theories include differences in ownership with larger firms which might impact strategy and management decisions. Mansfield (1984) find that larger firms commonly focus on larger and more long-term projects and avoid risky projects. Dilling-Hansen et al. (1999), however, show that ownership structure only plays a subordinated role. Furthermore, the largest third mainly includes companies with global operations, which tend to be more decentralized with geographically dispersed departments. Kafouros (2005), state that this may influence the ability to capture innovations and knowledge from a broader geographical base of scientists and local knowledge. Nevertheless, Kafouros states that the difficulty of coordination and communication among decentralized firms could as well act in the opposite direction to R&D productivity. However, larger firms may also have larger resources and better access to financing making their ability to deal with unforeseen events stemming from the unpredictability of R&D projects better.

We observe that our regression model, based on significance levels of coefficients, R-squared values and F statistics seem to fit the small segment quite poorly and especially for the high-

technology and non-manufacturing sub-samples. Interestingly, the group that seems to yield the best model fit is the smallest third of the manufacturing subsample. Daum (2002 Part 1) states that our accounting system was largely developed in the era of industrial capitalism. Because of this, it seems feasible to suggest that the accounting system would be better at describing manufacturing companies. In extension, that would imply that markets are able to rely more on existing accounting information when valuing manufacturing companies, making our regression model a good fit for this group. Regarding small companies outside the manufacturing sector, a possible explanation for our findings would be that small companies are to a much greater extent valued on factors other than the accounting variables used in our model. Looking at tables, 3, 4 and 5 we can see that there are much fewer observations in our sample for 1999 and 1998, affecting the size cutoff values a lot and especially for the smallest third of firms. This could potentially distort our findings for the small firms and is a potential source of error that could explain why the regression model's fit was poor within this subsample. However, we did check for how the regression output would change if excluding the observations for 1999 and 1998 from our sample and found no reason to believe that including these years distorts the results.

6.3 Manufacturing versus non-manufacturing

Overall, we see that manufacturing firms yield the greatest market value benefit from R&D when looking at all sizes combined. This is true when comparing with the non-manufacturing firms as well as the whole sample group. The results are in line with our hypothesis and with previous research. There is some ambiguity as to our results for the manufacturing sector when observing the size-categories individually. The most surprising result stems from the manufacturing firms within the largest third of firms. In this sub-group, we observe insignificant results for all but the Profitability variable, which is highly significant and of great importance for explaining Tobin's Q. The reason for this remains unknown, however, we believe it may relate to considerably greater adoption of the buy-externally approach amongst mature, profitable manufacturing companies. This enables large firms to leverage other companies' R&D efforts and reduce the risk of internal R&D investments that later prove to have inherently low value. This approach may be economically beneficial, at least in the shorter term, which might be another reason why larger companies, with more external pressure from analysts and investors, adhere to this approach.

However, to maintain focus on the manufacturing segment and not size in this part of the discussion, we believe the most important conclusions to be drawn here are for all size-categories across the manufacturing sample. It might be unsurprising that manufacturing firms yield greater benefits from improving products or processes through R&D. The relative impact of product and process innovation to companies engaging in the production of goods, process industries and product manufacturing is naturally greater for these firms. Durable goods are often manufactured in batches while non-durables are often produced in continuous process plants. For these production facilities, R&D relating to manufacturing processes (as opposed to e.g., R&D for products) should be of great importance to generate competences needed to absorb new processing equipment and technology (Ettlie, 1998). These production processes likely vary by industry and should generate a significant advantage regarding either or all of product quality, cost of manufacturing, reliability, and agility of production. For other niches within manufacturing, the product R&D may be of greater importance. This would likely be true for firms that manufacture highly complex and expensive products.

One should bear in mind that non-manufacturing firms may have neglectable total assets and highly limited process or product offering that could be leveraged using R&D, as traditionally defined. For instance, a consultancy business may be indifferent between intangible assets generated by R&D. Instead, their way of generating firm value is rather improvements of services performed. Our model will fail to capture these "investments" that may be relevant to improve services (e.g., personnel training), as they need to be recognized as costs rather than intangible assets.

6.4 High-technology versus low-technology

High-technology firms show the second highest importance of R&D intensity for firm value in our sample when looking at all sizes. There is some ambiguity when observing the size-categories individually, however, we believe the full sample provides the best statistics to draw conclusions from. Specifically, it is surprising that largest third of firms do not show the same patterns as when looking at the full sample. In fact, low-technology firms show greater importance of R&D when looking at the largest sub-sample. This might be of the preference of adapting the buy-externally approach, along the line of reasoning for manufacturing firms in the previous section. Also, it may

relate to a great amount of manufacturing firms belonging to the low-technology category, which is the category showing general higher importance of R&D than the high-technology sub-sample.

It is important for high-technology firms to be innovative. This innovation may not necessarily be best represented by R&D spending. However, we believe some effects are present and indicated by the results. One should bear in mind that the high-technology segment includes both internet and software companies and more general technologically advanced companies (e.g., Ericsson, Saab, Hexagon). Kafouros (2005) suggested future research to focus on productivity benefits from the then emerging internet companies (his study was performed on data for the years 1989-2002). Our sector classification cover these but also include a broader definition of the term. We believe there might be an inherent bias within the hardware-focused sub-category to partition R&D activities more clearly as opposed to other firm activities. For software companies, on the other hand, it might be less obvious what is the actual R&D activities and e.g., maintenance activities for code or similar. It would be interesting for future research to investigate the differences of internet-based companies more specifically to further investigate the specifics of this segment.

Since the R&D intensity median value is about 4 times higher for the high-technology category (53.6%) than the low-technology category (12.7%), we observe that R&D activities seem to play a relatively larger role. It should be noted, however, that R&D intensity is the ratio between the R&D stock and total assets and might be distorted because of lower relative total assets for the high-technology firms. However, we believe this could show that the pace of innovation is higher for high-technology firms and that the market thus values the R&D activities within this sub-sample higher than low-technology firms. Again, this is not true for all size-categories but holds true when looking at all sizes of firms combined.

7. Conclusions

This study examines the value of internally generated intangible assets from R&D spending. We further investigate the impacts of different business characteristics on the market value generated from R&D efforts. We gathered quantitative data for Swedish listed companies to perform a regression on 233 different companies during a 20-year period, 1998-2017, with total valid observations amounting to 1,872. The dependent variable in our regression was an operations-

focused Tobin's Q, the ratio of enterprise value to book value of capital employed. The independent variable of particular interest was an emulated balance sheet item, R&D stock, divided by total assets, called R&D intensity. The stock measure of R&D is based on previous research and assumes a depreciation rate of 15% to account for the obsolescence of these investments. Other independent variables used, because of their expected role in market valuations, were Sales Growth, Leverage and Profitability.

Within our framework, we find support for all four hypotheses presented. The hypotheses were based on previous research using the market value approach, with the exception of H_4, which was inspired by a productivity approach study. In line with prior studies, we find a systematic bias on enterprise value exceeding the firm's book value of capital employed (Tobin's Q > 1). An explanatory variable used to explain this shadow value is the internally-generated R&D stock intensity estimating intangible asset intensity, as we hypothesized that intangible assets have values not accounted for in the company's financial statements. Further, we find support for our partitions stating that R&D should be of greater importance for H_2) larger companies, H_3) manufacturing companies, and H_4) high-technology companies. However, this tendency is seemingly not that clear for small firms outside of the manufacturing sector.

To the best of our knowledge, analyzing the market value of R&D activities is largely unexplored on the Swedish market. Furthermore, we have expanded the research field by applying the market value approach to observe the differences between high-technology versus low-technology companies. Given this study's contribution to the research field of intangible asset valuation, we believe it can be of value for scholarly knowledge and policy-making. The discrepancy between the assumed fair value of intangible assets and the book value of the same indicate, and as stated in Barth et al. (2002), that intangible assets are largely unrecognized by the current accounting systems. We investigated different approaches to estimating internally generated intangible assets using the information that is currently widely available, and found accounting R&D reporting, intellectual property rights and advertising spending. These estimates are certain types of inputs into creating intangible assets (R&D and advertising spend) and legal ownership instruments (IP rights) and does not provide an accurate portrayal of actual intangible asset values. If accounting reporting provided more extensive and accurate information on intangible assets, we believe this would make the market able to value these assets more accurately and thus promote both lower

volatility in financial markets and reduced information asymmetry. Naturally, any intervention in the accounting system with this purpose would need to handle the issues relating to inherent characteristics of intangible assets. These include non-compliance with traditional laws of economics and the potential ownership dilution that may occur when knowledge is communicated.

Finally, we would like to present some of the ideas for extending the research field that we have pondered during the research process. Regarding our high-technology partition, further segmentation to isolate internet companies could provide deeper understanding for how this modern and dynamic part of the economy engages with intangible assets. Especially so when considering the nature of software. It could also be interesting to incorporate effects caused by practicalities of the stock market affecting efficient market assumptions which our Tobin's Q rationale builds on. For example, institutional investors may be subject to limitations as to which sizes of companies they are allowed to invest in because of factors such as stock liquidity. Different sectors and other sector definitions could also be utilized to investigate other industry specific tendencies. New estimates of intangible asset levels should be of interest and including more qualitative sourcing of intangible asset estimates may potentially be used to create more accurate estimates.

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9. Appendices

Appendix A. Driscoll-Kraay robust standard errors

FIRM SIZE AND CATEGORY	Intercept	R&D stock	Sales Growth	Leverage	Profitability
All observations					
Small	0.282	0.193	0.119	0.463	0.296
Mid	0.580	0.364	0.224	0.821	1.318
Large	0.644	0.774	0.826	0.985	0.958
All sizes	0.412	0.206	0.161	0.521	0.423
Manufacturing firms					
Small	0.478	1.219	0.382	0.348	1.062
Mid	0.684	2.636	2.200	1.358	3.602
Large	0.231	0.411	0.796	0.433	0.913
All sizes	0.319	1.282	0.423	0.264	0.863
Non-manufacturing firms					
Small	0.286	0.221	0.115	0.500	0.408
Mid	0.686	0.348	0.207	0.887	1.338
Large	1.457	0.804	0.975	2.110	3.293
All sizes	0.513	0.203	0.149	0.626	0.582
High-technology firms					
Small	0.365	0.283	0.349	0.593	0.406
Mid	0.710	0.732	1.096	0.952	2.864
Large	6.579	0.355	0.727	8.266	4.924
All sizes	0.555	0.293	0.688	0.714	1.142
Low-technology firms					
Small	0.211	0.235	0.097	0.421	0.469
Mid	0.633	0.275	0.173	0.827	1.653
Large	0.545	0.530	0.539	0.789	1.190
All sizes	0.282	0.166	0.091	0.304	0.425

Note: the table shows Driscoll-Kraay robust standard errors for all independent variables and the intercept

Appendix B. VIF test

VARIABLES	VIF	1 / VIF
R&D intensity	1.54	0.648
Sales Growth	1.49	0.670
Leverage	1.03	0.967
Profitability	1.02	0.980
Mean VIF	1.27	

Note: the table reports the result from a multicollinearity test (Variation Inflation Factor)

Appendix C. Table of all companies

#	Company	Sector	#	Company	Sector
1	TELEFONAKTIEBOLAGET LM ERICS	Electronic Technology	61	HANSA BIOPHARMA AB	Health Technology
2	ATLAS COPCO AB	Producer Manufacturing	62	PERSTORP AB	Process Industries
3	VOLVO AB	Producer Manufacturing	63	ESSELTE AB	Producer Manufacturing
4	TELIA COMPANY AB	Communications	64	ITAB SHOP CONCEPT AB	Producer Manufacturing
5	ASTRA AB	Health Technology	65	ALIMAK GROUP AB	Producer Manufacturing
6	ESSITY AKTIEBOLAG	Consumer Non-Durables	66	INWIDO AB	Non-Energy Minerals
7	SCA-SVENSKA CELLULOSA AB	Process Industries	67	DUNI AB	Consumer Durables
8	ASSA ABLOY AB	Producer Manufacturing	68	NISCAYAH GROUP AB	Commercial Services
9	SCANIA AB	Consumer Durables	69	TELELOGIC AB	Technology Services
10	SANDVIK AB	Producer Manufacturing	70	RAYSEARCH LABORATORIES AB	Commercial Services
11	HEXAGON AB	Electronic Technology	71	ARCAM AB	Producer Manufacturing
12	SKF AB	Producer Manufacturing	72	HMS NETWORKS AB	Technology Services
13	ELECTROLUX AB	Consumer Durables	73	AFRY AB	Commercial Services
14	ALFA LAVAL AB	Producer Manufacturing	74	CONCENTRIC AB	Producer Manufacturing
15	SKANSKA AB	Industrial Services	75	SCANDI STANDARD AB	Consumer Non-Durables
16	BOLIDEN AB	Non-Energy Minerals	76	OREXO AB	Health Technology
17	GETINGE AB	Health Technology	77	TRADEDOUBLER AB	Technology Services
18	LATOUR INVESTMENT AB	Producer Manufacturing	78	TOBII AB	Electronic Technology
19	SWEDISH MATCH AB	Consumer Non-Durables	79	BIOGAIA AB	Health Technology
20	MEDA AB	Health Technology	80	BIOTAGE AB	Health Technology
21	TRELLEBORG AB	Producer Manufacturing	81	HALDEX AB	Producer Manufacturing
22	SSAB CORP	Non-Energy Minerals	82	INTENTIA INTERNATIONAL AB	Technology Services
23	HUSQVARNA AB	Consumer Durables	83	CAMURUS AB	Health Technology
24	KINNEVIK AB	Finance	84	PROBI AB	Health Technology
25	SAAB AB	Electronic Technology	85	SINCH AB (PUBL)	Communications
26	NIBE INDUSTRIER AB	Consumer Durables	86	NET INSIGHT AB	Electronic Technology
27	GAMBRO AB	Health Technology	87	KARO PHARMA AB	Health Technology
28	AGA AB	Process Industries	88	PERBIO SCIENCE AB	Health Technology
29	FINGERPRINT CARDS AB	Technology Services	89	BIACORE INTL AB	Health Technology
30	SWEDISH ORPHAN BIOVITRUM AB	Health Technology	90	OPUS GROUP AB	Electronic Technology
31	DOMETIC GROUP AB	Producer Manufacturing	91	GUNNEBO AB	Electronic Technology
32	HEXPOL AB	Producer Manufacturing	92	IBS AB	Technology Services
33	INDUTRADE AB	Producer Manufacturing	93	CISION AB	Commercial Services
34	LIFCO AB	Finance	94	VBG AB	Producer Manufacturing
35	ENIRO GROUP AB	Commercial Services	95	NEDERMAN HOLDING AB	Producer Manufacturing
36	HOLMEN AB	Process Industries	96	CELSIUS AB	Electronic Technology
37	AXIS AB	Technology Services	97	INVISIO AB	Electronic Technology
38	KINNEVIK INDUSTRIFORVLTNINGS	Finance	98	CELLAVISION AB	Technology Services
39	THULE GROUP AB	Consumer Durables	99	NELLY GROUP AB	Commercial Services
40	SECO TOOLS AB	Consumer Durables	100	BALLINGSLOEV INTERNATIONAL	Consumer Durables
41	BEIJER ALMA AB	Producer Manufacturing	101	ANOTO GROUP AB	Electronic Technology
42	LINDAB INTL AB	Producer Manufacturing	102	G5 ENTERTAINMENT AB	Technology Services
43	NOLATO AB	Process Industries	103	MEDIVIR AB	Health Technology
44	AB FAGERHULT (PUBL)	Producer Manufacturing	104	ADDNODE GROUP AB	Technology Services
45	VITROLIFE AB	Health Technology	105	TRANSMODE AB	Technology Services
46	SVEDALA INDUSTRI AB	Producer Manufacturing	106	PERGO AB	Consumer Durables
47	ACTIVE BIOTECH AB	Health Technology	107	KALMAR INDUSTRIES AB	Producer Manufacturing
48	CARDO AB	Distribution Services	108	BJORN BORG AB	Consumer Non-Durables
49	ARJO AB	Distribution Services	109	ALLGON AB - OLD	Electronic Technology
50	CLOETTA AB	Consumer Non-Durables	110	IAR SYSTEMS AB	Technology Services
51	Q-MED AB	Health Technology	111	ORC GROUP AB	Technology Services
52	HOGANAS AB	Non-Energy Minerals	112	FORTNOX AB	Technology Services
53	PARADOX INTERACTIVE AB	Technology Services	113	SENSYS GATSO GROUP AB	Electronic Technology
54	MYCRONIC AB	Electronic Technology	114	XVIVO PERFUSION AB	Health Technology
55	INDUSTRIAL & FINL SYSTEMS AB	Technology Services	115	STUDSVIK AB	Electronic Technology
56	MUNTERS GROUP AB	Producer Manufacturing	116	GOMSPACE GROUP AB	Electronic Technology
57	ATLE AB	Producer Manufacturing	117	WILSON THERAPEUTICS AB	Health Technology
58	GRANGES AB	Non-Energy Minerals	118	NORDIC WATERPROOFING HLDGS	Non-Energy Minerals
59	MUNTERS AB	Producer Manufacturing	119	KAROLIN MACHINE TOOL AB	Producer Manufacturing
60	BT INDUSTRIES AB	Producer Manufacturing	120	CTT SYSTEMS AB	Electronic Technology

#	Company	Sector
121	PRECISE BIOMETRICS AB	Electronic Technology
122	ENEA AB	Technology Services
123	STRALFORS AB	Technology Services
124	CONCEJO AB (PUBL)	Electronic Technology
125	BEIJER ELECTRONICS GROUP AB	Electronic Technology
126	CINNOBER FINANCIAL TECH	Technology Services
127	BIOINVENT AB	Health Technology
128	POWERCELL SWEDEN AB	Utilities
129	DORO AB	Electronic Technology
130	SVEDBERGS I DALSTORP AB	Consumer Durables
131	AEROCRINE AB	Electronic Technology
132	PROTECT DATA AB	Technology Services
133	KABE GROUP AB	Consumer Durables
134	MIDWAY HOLDING AB	Consumer Durables
135	ZETECO AB	Producer Manufacturing
136	MOBERG PHARMA AB	Health Technology
137	HL DISPLAY AB	Producer Manufacturing
138	ALLIGATOR BIOSCIENCE AB	Health Technology
139	BOULE DIAGNOSTICS AB	Health Technology
140	ABLIVA AB	Health Technology
141	MICRO SYSTEMATIONS AB	Technology Services
142	IMMUNOVIA AB	Health Technology
143	KAROLINSKA DEVELOPMENT AB	Finance
144	GEVEKO AB	Process Industries
145	PRICER AB	Technology Services
146	TRENTION AB	Utilities
147	MIPS AB	Consumer Non-Durables
148	TELIGENT AB	Technology Services
149	BIOPHAUSIA AB	Health Technology
150	ELOS MEDTECH AB	Electronic Technology
151	FM MATTSSON MORA GROUP AB	Producer Manufacturing
152	IRLAB THERAPEUTICS AB	Health Technology
153	READSOFT AB	Technology Services
154	EDGEWARE AB	Technology Services
155	SINTERCAST AB	Producer Manufacturing
156	GLYCOREX TRANSPLANTATION AB	Health Technology
157	AUDIO DEV INFORMATIONSTEKNIK	Electronic Technology
158	ARTIMPLANT AB	Health Technology
159	BRIO AB	Consumer Durables
160	ACAP INVEST AB	Miscellaneous
161	LAMMHULTS DESIGN GROUP AB	Producer Manufacturing
162	NEXAM CHEMICAL AB	Process Industries
163	PROFILGRUPPEN AB	Non-Energy Minerals
164	NUEVOLUTION AB	Health Technology
165	OBDUCAT AB	Electronic Technology
166	ORTIVUS AB	Distribution Services
167	GYLLING OPTIMA BATTERIES AB	Producer Manufacturing
168	ORGANOCLICK AB	Process Industries
169	BIOSENSOR APPLICATIONS	Health Technology
170	ENZYMATICA AB	Health Technology
171	SKANE MOLLAN AB	Process Industries
172	KANCERA AB	Health Technology
173	DUROC AB	Producer Manufacturing
174	CUSTOS AB	Miscellaneous
175	CONTEXTVISION AB	Health Technology
176	FREJA EID GROUP AB	Commercial Services
177	PAYNOVA AB	Technology Services
178	PIEZOMOTOR UPPSALA AB	Electronic Technology
179	CHERRY AB	Consumer Services
180	XBRANE BIOPHARMA AB	Health Technology
181	BONESUPPORT HLG	Health Technology
182	ELEKTRONIKGRUPPEN BK AB	Electronic Technology
183	NORDIFAGRUPPEN AB	Producer Manufacturing
184	HUMAN CARE H C AB	Health Technology
185	PREVAS AB	Technology Services
186	JEEVES INFORMATION SYSTEM AB	Technology Services
187	BIORA AB	Health Technology
188	SERSTECH AB	Electronic Technology
189	AVAILO AB	Commercial Services
190	SURGICAL SCIENCE	Health Technology
191	ADVENICA AB	Technology Services
192	SENEA AB	Electronic Technology
193	HOVDING SVERIGE AB	Consumer Durables
194	TRIO AB	Communications
195	EPISURF MEDICAL AB	Health Technology
196	FME EUROPE AB	Transportation
197	GLOBAL IP SOLUTION	Technology Services
198	STILLE AB	Health Technology
199	CASSANDRA OIL AB	Energy Minerals
200	BIOLIN SCIENTIFIC AB	Health Technology
201	IMAGE SYSTEMS AB	Technology Services
202	SIVERS SEMICONDUCTORS AB	Electronic Technology
203	SENSODETECT AB	Health Technology
204	TOPRIGHT NORDIC AB	Commercial Services
205	MULTIQ INTERNATIONAL AB	Electronic Technology
206	ZETADISPLAY AB	Producer Manufacturing
207	MEDIROX AB	Health Technology
208	ALLGON AB	Electronic Technology
209	PROSTALUND AB	Health Technology
210	SCIBASE HOLDING AB	Health Technology
211	DIFFCHAMB AB	Process Industries
212	JLT MOBILE COMPUTERS AB	Electronic Technology
213	PHOTOCAT AS	Process Industries
214	XINTELA AB	Health Technology
215	ZAPLOX AB	Technology Services
216	NORDIC SERVICE PARTNERS HLDG	Consumer Services
217	MEDICANATUMIN AB	Retail Trade
218	ALTECO MEDICAL AB	Health Services
219	SAXLUND GROUP AB	Producer Manufacturing
220	XAVITECH AB	Producer Manufacturing
221	AQERI HOLDING AB	Electronic Technology
222	MIRIS HOLDING AB	Electronic Technology
223	CYBAERO AB	Electronic Technology
224	NISCHER PROPERTIES AB	Finance
225	NETWISE AB	Technology Services
226	GAMING CORPS AB	Technology Services
227	STAR VAULT AB	Technology Services
228	WESTPAY AB	Electronic Technology
229	EXAVE AB	Consumer Durables
230	PARANS SOLAR LIGHTING AB	Producer Manufacturing
231	CHRONTECH PHARMA AB	Finance
232	CHEMEL AB	Health Technology
233	CREATIVE ANTIBIOTICS SWEDEN	Health Technology