Factors Determining Wealth Creation from Divestitures in Sweden

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Abstract

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Divestitures have grown in importance and popularity over the years, rivaling other strategic transactions in mergers and acquisitions. The dominating opinion in academic research is that divestitures overall generate an abnormal return for the parent company stock. This thesis will focus on how Swedish companies perform in the short-term around the announcement of a divestiture. A multiple linear regression analysis finds significance for divestiture gains being attributed to companies focusing on core competencies and to companies with low returns on assets and high returns on equity. However, no significance is found for the size of the companies or financial distress.

Keywords: Divestiture, refocusing hypothesis, size effect, ROA, ROE, Equity Ratio, Financial Distress, Optimal Portfolio Management
Sammanfattning

Faktorer som påverkar överavkastningen på avknopplingar i Sverige

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1. Introduction

The study on divestitures has a long history with a rich collection of previous research. The results in this thesis consist of two parts, the first based on an event study where the results will be used to form the response variable for part II.

In this introduction, the study of divestitures is introduced. The intended main output is explained and the scope and problem formulations presented.

1.1 Background and Problem Discussion

During a long period of time, corporate acquisitions have been the dominant form of M&A transactions. It seems that every year we hear about record number of deals made globally, each year being surpassed by the next. These types of transactions occur even though there is now a dominant theory that shareholders handle diversification better than companies themselves. The theory instead suggests that companies should focus on their core capabilities and leave the diversification to investors (Brealey et al., 2013, p. 812). With this in mind maybe, there is another trend brewing. That of demergers; selling off business units to become smaller. Swedish angel investor Christer Gardell certainly seems to believe so (Gardell, 2016). He believes that divestitures are the next big trend in the M&A market, arguing that the days of the European conglomerates are over.

A divestiture is defined as measures through which a company can adjusts its ownership structure and reduce its business portfolio scope by selling business units or subsidiaries (Brauer and Schimmer, 2010).

The theory of divestitures is not new, the fact that divestitures create shareholder value was established more than 30 years ago (Miles and Rosenfeld, 1983). Although, historically, it was not given as much attention as other forms of transactions. While divestiture have certainly been researched to some extent it was not until around the middle of the last decade it really gained traction, before that divestitures were often treated as side aspects (Brauer, 2006).

The extensive research on the financial performance of divestiture that exists today agree upon one central thing: The stock price of the divested parent company generates an abnormal return in the days surrounding the initial deal announcement. However, the positive results have been found to vary substantially among data sets (Brauer and Schimmer, 2010).

This big variance in the positive effects leaves room for the question, what exactly causes the market to reward the decision to divest? Since the results vary to such an extent, a logical
assumption could be that certain factors are rewarded more than others. And this question is at the heart of this bachelor thesis.

This paper is not the first to investigate the contribution of individual factors to the divestiture process. There are two principle theories that are believed to explain the positive abnormal returns from divestiture 1) improving fit and or focus and 2) reducing the cost of financial distress (Lasfer et al., 1996). Another paper investigated factors such as whether parent companies considered large receive higher abnormal returns, known as the size effect (Tubke, 2005). But the study of Swedish companies in particular has not been looked at to the same degree the U.S and other European countries have.

1.2 Problem Formulation

Studying the Swedish market, which of the factors that have shown to influence divestiture gains when studying global corporations have an impact on Swedish corporations? This will be presented by the hypotheses below. Further descriptions of these hypotheses are found in chapter two. In addition to these hypotheses, I investigate the relations between divestiture gains and two industries, healthcare and industrials.

**Hypothesis 1:** Stock price response is significantly higher for asset divestitures made by parent companies that are large (The Size effect).

**Hypothesis 2:** Stock price response is significantly higher for asset divestitures made by financially distressed companies.

**Hypothesis 3:** Stock price response is significantly higher for asset divestitures made by parent companies with high ROA.

**Hypothesis 4:** Stock price response is significantly higher for asset divestitures made by parent companies with high ROE.

**Hypothesis 5:** Stock price response is significantly higher for asset divestitures made by companies divesting non-core assets to focus on core activities. (Refocusing Hypothesis)

1.3 Purpose

The purpose of this thesis is to look at certain factors that have directly or indirectly been investigated in previous research and determine if they can be found to have a significant impact on Swedish companies. On a more general level this paper aims to contribute to the
idea that divestitures will be increasingly popular because companies are focusing on core competencies.

These questions are important to look at to determine if divestitures are in general a strategically good idea or rather will be contingent on the environment the company finds itself in.

1.4 Scope

This thesis will only look at divestitures made by Swedish companies registered on Nasdaq Stockholm from 2005 until 2018 with the success measured only in the short-term. The information regarding a divestiture is collected only around the first announcement date and any subsequent deal information such as the prospectus has thus not been taken into account. The timing of the first press release has been considered since if it came at the close of market, the next trading day will be considered the announcement day to properly measure the 1-day return. The data set consist only of spin-offs and equity-carve outs where the divested parent lists the subsidiary on the public market. There will be no consideration of which of these two deal structure a given divestiture is. The subsidiary in turn does not have to be Swedish or listed on a Swedish stock-exchange. For most of the data the divested company will be situated in Sweden, but for some of the data the divested company acts outside Sweden. In literature there are numerous potential factors determining the success of a divestiture. This thesis is limited to some of those that are most quantifiable and thus possible to mathematically evaluate. There are limitations in the data that limit the possible factors to investigate; this will be further explained in chapter 4.

1.5 Target Audience

The intended audience of this paper is other students interested in M&A and professionals looking at the strategic benefits for divestitures by Swedish companies. Hopefully this thesis will provide information and motivation to further explore divestitures in the Nordics with bigger datasets and a longer-term perspective.

1.6 Report Structure

This thesis begins with an introduction, explaining the current situation in the study of divestiture and formulating the problem and scope of the thesis. The next two chapters introduce the theory that will form the basis of the research. In chapter 2 I also mention some of the previous student research that has been conducted in the Nordics regarding divestitures.
Chapter four then present the data and the methodology to evaluate the data and quantify a successful divestiture. The multiple linear regression model and key definitions are introduced. In Chapter 5 the results for the Part I and the regression part are presented. For Part II the results begin with a residual analysis leading up to the final model. At the end of Part II two further dummy variables for industry are investigated that are not based on previous research but introduced for this thesis specifically. The analysis of the results comes in chapter 6. Finally, the conclusions from the results in chapter 7, with caveats for the possible weaknesses and suggestions for future research. The full sets of references are in chapter 8 and the appendix consists of the data tables.
2. Theoretical Framework (Financial)

By reviewing theory and previous research I have found certain factors that could determine the abnormal return from divestitures for the divested parent company. In this section the underlying theory that my results will be based on are presented. Some assumption on how the market works are necessary to be able to draw any conclusions.

2.1 Efficient Market Hypothesis

The efficient market hypothesis (EMH) states that current price of company stock reflects all available information regarding the value of the firm, thereby making it impossible to earn excess returns, where excess returns is defined as the amount of return above the overall market. The hypothesis further suggests that the main engine behind price changes is the arrival of new information. The market is then said to be efficient because the prices adjust quickly, leaving no time for anyone to act on the new information. Because of this, the price of a security perfectly reflects all available information and so there is no reason to believe a stock is either undervalued or overvalued (Clarke et al., 2001).

The critique against the efficient market hypothesis raised in 1970s was that it was too broad to empirically investigate. Therefore, its creator Eugene Fama specified three forms of the hypothesis: a weak, semi strong and a strong form.

Weak form

The weak form of the hypothesis states that all historical information is reflected in the stock price and that you cannot generate a return to cover transaction costs (Fama, 1970). Another word for the weak form of market efficiency is the random walk hypothesis which states that successive price movements should be independent. This hypothesis has been tested in some studies by examining the correlation of individual securities over two time periods, the current period and a previous one. A positive serial correlation would indicate continuation, that is a that a positive abnormal return is likely to be followed by another positive abnormal return and vice-versa for negative correlations, which in turn would be a trend towards reversal. We would expect zero correlation in the case that this weak form of the hypothesis was true (Clarke et al., 2001). A study on the serial correlations coefficients of a sample of American stocks found statistical significance but not enough to cover the transaction costs of trading (Fama, 1965) and indeed gave empirical credence to this form of the hypothesis.
**Semi-strong form**

The Semi strong hypothesis has been the most controversial and subsequently attracted the most attention. This form of the hypothesis states that all publicly available information is reflected in the stock price, both historical information and any information that was released 1 minute ago. This implies that no one can gain excess return by trading actively to the market, even though you would respond within second of an announcement (Clarke et al., 2001).

**The strong form**

Finally, the strong form of the hypothesis has been empirically tested by looking at the profitability of insider trading. So, in addition to the assumption in the above weaker forms, the strong form also includes any information that is not publicly available. Which means that you cannot make a profit even though you have access to insider information. This form of the hypothesis has been the most criticized. (Clarke et al., 2001). There has been considerable evidence that insider trades are indeed profitable (Jaffe, 1974) and thereby disproving this form.

As a conclusion, to interpret the results in this thesis assumptions must be made on the efficiency of the market. If I assume that the market is semi-efficient I can say that any abnormal return reflects the actual change of wealth from the divestiture, thus giving a way to measure “success”.

### 2.2 Size Effect

One possible factor determining the success of divestiture comes from the Size Effect. As previously mentioned, Tubke looked at the size of the divested parent company but found no significance (Tubke, 2005). The Size effect has been looked at in the field of acquisition returns specially. The effect on acquisition returns was investigated by the size of the company. By using a dummy variable with a large corporations being characterized as belonging to the 75th percentile of the companies on the stock exchange during the year of the deal (Moeller et al., 2004). Subsequent studies by the same authors then found significant explanatory effect (Moeller et al., 2005). A Similar study looking at stock-financed acquisitions found that the relative size of a firm had significant explanatory power (Golubov et al., 2015).
This research gives rise to Hypothesis 1.

**Hypothesis 1**: Stock price response is significantly higher for asset divestitures made by parent companies that are large (The Size effect).

### 2.3 Financial Distress

There is not an agreement in research on whether financial distress has a positive or negative effect on divestiture gains. In this subsection both sides will be presented.

Financial distress is defined as a situation where a firm incurs an amount of debt that its firm size, profitability and asset composition cannot sustain. This results in liquidity problems and subsequently affects its ability to pay long-term debts and long-term fixed expenses which causes insolvency (Lin et al., 2008, p. 542).

Financial distress has been studied as a possible contributor to the abnormal return generated from divestitures. In some of those studies, debt ratios have been used as a proxy to financial distress (Gilson and Vetsuypens, 1993). One study used the debt ratio to investigate the effect of positive effect of financial distress on the cumulative abnormal return and found support for financial distress as a positive factor in divestiture gains (Laamanen et al., 2014). Another study looking at UK divestures found that financial distress led to abnormal return above that of a general divestiture indicating that at least in the UK, the main benefit of divestitures comes in resolving issues regarding the divested parent companies’ financial health. Thereby they found support for the argument that efficient monitoring by lenders leads to divestiture being value-enhancing corporate decisions (Lasfer et al., 1996).

However, researchers are not unified in the positive effect of financial distress on the outcome of the divestiture. The empirical evidence on shareholder gains from paying down debt is inconclusive (Brown et al., 1994; Lang et al., 1995). One paper determined that the impact from a divestiture could be negative in situations where the liabilities exceed the market value of the company’s total assets. In this scenario, the shareholders of this company hold what can be compared to a call option on the firm’s assets. If the firm decides to sell of a part of those assets the call option ceases to exist which will be received negatively by the investors (Brown et al., 1994). Another argument is that in instances where financial distress affects the entire industry there will be no buyers in the same sectors leaving the seller forced to sell outside the industry. As a result, they will be forced to sell at a discount since these potential buyers will have less use of the assets (Shleifer and Vishny, 1992).
Lastly, a key way in which financial distress can affect the outcome is through signaling. Information asymmetry in the capital markets can cause signaling to impose a cost on divestiture decision. Because managers know more than outside investors, these investors will make assumptions on a company’s future performance based on the management decisions. A divestiture decision that is born from wanting to remove business units that do no generate a required return on equity may be incorrectly perceived by outside investors as a need to urgently inject cash due to financial distress, resulting in a decline in the share price (corporate finance institute, 2018).

Given the use of debt ratios as a proxy for financial distress, this gives rise to the 2nd hypothesis:

**Hypothesis 2:** Stock price response is significantly higher for asset divestitures made by financially distressed companies.

### 2.4 Optimal Portfolio Management

Given a set of factors, including projections on future income and potential sale values one can determine the optimal time for an asset with traditional economic analysis. An issue may arise if policy directives in a company dictate certain levels of return on equity must be met each year. In this scenario some assets may be sold at an inopportune time to meet those financial requirements. Thereby, optimal portfolio management strategies are not followed (Bean, 1984).

This leads to hypothesis 3 and 4 that has been constructed to this specific thesis. The argument is that if a company has low key financial metrics such as ROE the year before the divestiture that may lead them to sell an asset at an uneconomic time leading to a stock price fall.

**Hypothesis 3:** Stock price response is significantly higher for asset divestitures made by parent companies with high ROA.

**Hypothesis 4:** Stock price response is significantly higher for asset divestitures made by parent companies with high ROE.
2.5 Refocusing Hypothesis

Previous studies have found that over-diversification has been a main factor driving divestitures (Brauer, 2006). Research has also shown that announcement stock returns are greater for companies increasing focus (John and Ofek, 1995). Specially, this refocusing is believed to reduce managerial inefficiencies such as owner-manager conflict of interests and operational inefficiencies because the refocusing would allow enhanced financial resource allocation (Afshar et al., 1992; John and Ofek, 1995, Schipper and Smith, 1983). Furthermore, research has suggested that the number of business segments in a parent company before the divestiture, has a positive relationship with the stock market reaction of the announcement (Vijh, 1999). Similarly, it has been theorized that a firm reducing from eight to seven business units has a bigger positive effect than a firm reducing from two to one. (Dittmar and Shivdansani, 2003; Lang and Shulz, 1994).

This hypothesis is closely related to the pure play hypothesis that suggest that the value in a divestiture is created from splitting up the different business segments of the parent and the subsidiary and thus helping the market to analyze and understand the companies separately better (Schimmer, 2012). From this our last hypothesis is presented.

**Hypothesis 5**: Stock price response is significantly higher for asset divestitures made by companies divesting non-core assets to focus on core activities.

2.6 Previous Research on Negative Excess Returns from Divestitures

To form a balanced perspective on the research it is necessary to point out that while many studies have found wealth creation from divestitures, there have been some studies showing the opposite. One such study examined the effect of divestitures of South African business units on firm value and found negative and significant excess return accrue the shares of the parent company at announcement (Wright and Ferries, 1997). One of their theoretical explanations was that senior executives may respond to external political pressure and adopt strategies that are costly to shareholders. Thus, noneconomic pressures can influence corporate strategies resulting in divestiture that are not motivated by value-enhancement goals.
2.7 Student Theses

In Sweden, previous student theses about divestitures include Dansehvar, Johansson and Nordin (2005) at Handelshögskolan in Göteborg that compared stock price reaction between an equity carve-out and a spin-off focusing on the divested company instead of the parent, finding significant abnormal return in both cases. Albertson, et al (2008) at Lunds University focused on the parent company looking at short term price reaction to divestiture announcement and found significant positive abnormal return. Bergman and Wass (2017) at Uppsala University looked at both the parent company and subsidiary. Their results for the subsidiary was consistent with previous research on short-term gains while they found negative results one year after the announcement for the parent company, contrary to previous research. They concluded that the Swedish stock market reaction follows the global one in the short-term but not long-term. They also looked at if focusing on core activities can be a reason for divestiture success with inconclusive results.
3. Theoretical Framework (Statistics)

3.1 Multiple Linear Regression

A multiple regression model is used to model the relationship between a dependent variable and some independent variables. The independent variables are also called regressors or covariates. The dependent variable can also be referred to as the response variable. The linear equations are the following

\[ Y_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + \epsilon_i, \, i = 1, 2, ..., n, \quad (1) \]

where, \( Y_i \) is the \( i \)th dependent variable, \( \beta_0 \) is the intercept, \( \beta_j \) is the \( j \)th regression coefficient of a total of \( k + 1 \) regression coefficients including intercept. \( X_{ij} \) is the \( j \):th independent variable in the \( i \):th observation and finally, \( \epsilon_i \) is the \( i \)th the random error term and \( n \) is the total number of observations.

The regression model can be expressed in matrix form as

\[ Y = X\beta + \epsilon, \quad (2) \]

where

\[
\begin{bmatrix}
Y_1 \\
Y_2 \\
\vdots \\
Y_n
\end{bmatrix} =
\begin{bmatrix}
1 & X_{11} & X_{12} & \cdots & X_{1k} \\
1 & X_{21} & X_{22} & \cdots & X_{2k} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
1 & X_{n1} & X_{n2} & \cdots & X_{nk}
\end{bmatrix}
\begin{bmatrix}
\beta_0 \\
\beta_1 \\
\vdots \\
\beta_k
\end{bmatrix} +
\begin{bmatrix}
\epsilon_1 \\
\epsilon_2 \\
\vdots \\
\epsilon_n
\end{bmatrix}.
\]

\( Y \) is a \( n \times 1 \) vector of the \( n \) observations. \( X \) is a \( n \times p \) matrix consisting of the regressor variables where \( p = k + 1 \) is the number of regression coefficients including intercept. \( \beta \) is a \( p \) \( \times \) \( 1 \) vector of the regression coefficients. Finally, \( \epsilon \) is an \( n \times 1 \) vector of the random errors.

The Ordinary Least Square-method (OLS) is used to perform the regression analysis. The vector of least-squares estimators, \( \hat{\beta} \), are obtained by minimizing the sum of squares of the errors: \( \epsilon' \epsilon. \) This leads to the least-squares normal equations

\[ X'X\hat{\beta} = X'Y, \quad (3) \]

\[ \hat{\beta} = (X'X)^{-1}X'Y, \]
Two types of independent variables employed in a regression analysis are the quantitative variables and qualitative variables. A dummy variable is a qualitative variable, also known as an indicator variable. It takes the value 0 or 1 to indicate either the presence or absence of some categorical effect that can be expected to shift the outcome. Dummy variables are used in situations where it is fitting to separate the data into mutually exclusive categories such as the industry a company belongs to (Montgomery et al., 2012 p.280).

3.2 Model Assessment and Validation

3.2.1 Multicollinearity

Multicollinearity can impact the results from a regression analysis. It can be referred to as the near-linear dependence among the covariates. The presence of multicollinearity does not reduce the predictive power but it does affect the estimated coefficients by increased standard errors and thus uncertainty in their values (Montgomery et al., 2012 p.117).

One way to detect multicollinearity is by inspecting the correlation matrix of the regressors. This is done by first obtaining the unit length scaled values defined as

$$w_{ij} = \frac{X_{ij} - \bar{X}_j}{s_{jj}^{1/2}}, i = 1,2, ..., n, \quad j = 1,2, ..., k \quad (4)$$

where $k$ is the number of regressors not including intercept and $\bar{X}_j$ is the mean of the regressors variables in the $j$th row and $s_{jj} = \sum_{i=1}^{n}(X_{ij} - \bar{X}_j)^2$. By creating a matrix $W$ of the scaled values, the correlation matrix is obtained as

$$W'W = \begin{bmatrix} 1 & r_{12} & r_{13} & \cdots & r_{1k} \\ r_{12} & 1 & r_{23} & \cdots & r_{2k} \\ r_{13} & r_{23} & 1 & \cdots & r_{3k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{1k} & r_{2k} & r_{3k} & \cdots & 1 \end{bmatrix}$$

Another important multicollinearity diagnostic is the variance inflation factor (VIF). For the $i$th regressor it is defined as

$$VIF_i = \frac{1}{1 - R_i^2}, i = 1,2, ..., p \quad (5)$$
where \( R_i^2 \) is the coefficient of determination resulting from regressing the \( i \)th of the regressors onto the other regressor variables included in the model. The coefficient of determination is defined in section 3.2. VIF values larger than 10 can indicate presence of multicollinearity (Montgomery et al., 2012 p.118)

### 3.2.2 Influential Observations

Influential observations can affect the regression model by shifting the regression line towards that point (Montgomery et al., 2012 p.211). Two measures to detect influential points are Cook’s-Distance and the COVRATIO.

Beginning with Cook’s-Distance, an influential observation can be measured by the squared distance between the least-squares coefficient estimates based on all \( n \) data points \( \hat{\beta} \) and the estimates \( \hat{\beta}_{(i)} \) that are obtained by deleting the \( i \)th point. The general form of this measure is

\[
D_i = (M \cdot c) = \frac{(\hat{\beta}_{(i)} - \hat{\beta})' M (\hat{\beta}_{(i)} - \hat{\beta})}{c}, i = 1,2,\ldots,n, \tag{6}
\]

where \( M = X'X \), \( c = pMS_{res} \). \( X \) was defined above, \( p \) is the number of independent variables and \( MS_{res} \) is the residual mean square (Montgomery et al., 2012 p.215). The residual mean square is defined as

\[
MS_{res} = \frac{SS_{res}}{n - p}, \tag{7}
\]

where \( SS_{res} \) is defined in section 3.3.

To express the role of \( i \)th observation on the overall precision of estimation, I use the COVRATIO defined as

\[
COVRATIO_i = \frac{|(X_{(i)}'X_{(i)})^{-1}S_{(i)}^2|}{|(X'X)^{-1}MS_{res}|}, i = 1,2,\ldots,n \tag{8}
\]

where \( X_{(i)} \) is the regression variables with \( i \)th point removed and \( S_{(i)}^2 \) defined as

\[
S_{(i)}^2 = \frac{(n - p)MS_{res} - e_i^2/(1 - h_{ii})}{n - p - 1}, \tag{9}
\]

Where \( e_i \) is defined in equation (11) section 3.2.3 and \( h_{ii} \) is defined by equation (13) in the same section.
A high leverage point will make $COVRATIO_i$ large. The cutoff values for COVRATIO are not easy to obtain. A suggestion is

$$COVRATIO - 1 > \frac{3p}{n}, \quad (10)$$

where, $p$ is the number of covariates and $n$ number of observations. However these cutoffs are only recommended for large samples (Montgomery et al., 2012 p.219).

### 3.2.3 Residual Diagnostics

There are some key assumptions in the study of multiple regression models: (Montgomery et al., 2012 p.129)

1. An approximate linear relationship between the dependent variable and the independent variables.

2. The error term has zero mean and constant variance $\sigma^2$.

3. The errors are not correlated.

4. The errors are normally distributed.

The residuals are defined as

$$e_i = Y_i - \hat{Y}_i, \quad i = 1,2,\ldots,n \quad (11)$$

where $Y_i$ is the $i$th observation and $\hat{Y}_i$ the corresponding fitted value. Plotting the residuals is a good tool to investigate how well a regression model fits the data and verify the assumptions presented above. (Montgomery et al., 2012 p.130).

Studentized residuals are scaled residuals that are standardized and are helpful in detecting outliers or extreme values (Montgomery et al., 2012 p.131). They are defined as

$$r_i = \frac{e_i}{\sqrt{MS_{res}(1 - h_{ii})}}, \quad i = 1,2,\ldots,n \quad (12)$$

where $h_{ii}$ is the $i$th diagonal element of the hat matrix defined as

$$H = X(X'X)^{-1}X', \quad (13)$$
Quantile-quantile (QQ) plots are sample order statistics plotted against some theoretical quantiles form a standard normal distribution. Any systemic deviation from linearity apparent in the probability plot indicates non-normal data (Thode, H. p.21). The studentized residuals can be used in a QQ-plot to determine if the errors are normally distributed with the studentized residuals on the y-axis and the theoretical standard normal quantiles on the x-axes.

Finally, a partial regression plot is an enhanced way to study the marginal relationship of a regressor with the response variable holding the other regressors fixed (Montgomery et al., 2012 p.143).

### 3.2.4 Variable Transforms

To try and correct non-normality or non-constant variance of a regression model, the response variable can be transformed. One alternative to transform the variables is the Box-Cox Method. The power transform of the \( i \)th observation \( Y_t^{\lambda} \) is defined as

\[
Y_t^{(\lambda)} = \begin{cases} 
\frac{Y_t^\lambda - 1}{\lambda Y_t^{\lambda-1}}, & \lambda \neq 0 \\
\hat{Y} \ln(Y_t), & \lambda = 0
\end{cases}
\]

(14)

where \( \hat{Y} = \ln^{-1} \left( \frac{1}{n} \sum_{i=1}^{n} \ln Y_i \right) \) is the geometric mean of the observations and \( Y_t^{(\lambda)} \) is the new dependent variable. (Montgomery et al., 2012 p.182).

### 3.3 Model Selection

To select a good model, two available approaches are the all possible regression method and forward selection. The forward selection is an algorithm that fits the regressors to the response variable by beginning with no regressors except the intercept and then adding one at a time. The first regressor to enter the model is the one that has the largest simple correlation with the dependent variable (Montgomery et al., 2012 p.345).

The all possible regression method fits all possible combinations of the regressors and selects the best regression model according to some predefined criteria. For \( k \) regressors there are \( 2^k \) possible combinations to evaluate.

Two of those criteria are the \( R^2 \) and the adjusted \( R^2 \). The \( R^2 \) also known as the coefficient of determination is a measure of the goodness of fit a regression model. It stands for the proportion of the variance in the dependent variable that is predictable from the independent variables (Montgomery et al., 2012 p.87). First, \( R^2 \) is defined as
\[ SS_{res} = \sum_{i=1}^{n} (Y_i - \bar{Y}_i)^2, \quad (15) \]

\[ SS_T = \sum_{i=1}^{n} (Y_i - \bar{Y})^2, \quad (16) \]

\[ R^2 = 1 - \frac{SS_{res}}{SS_T}, \quad (17) \]

where \( \bar{Y} \) is the mean of the dependent variables, \( n \) total number of observations, \( Y_i \) is \( i \)th observation and \( \bar{Y}_i \) is the respective estimated value. Then with \( p \) explanatory variables, the adjusted \( R^2 \):

\[ R^2_{adj} = 1 - \frac{(n - 1)}{(n - p)} (1 - R^2), \quad (18) \]

Another criterion is The Schwartz Bayesian Information Criteria (BIC). Defined as

\[ BIC = \ln(n) p - 2 \ln(L) \quad (19) \]

where, \( L \) is likelihood function for a specific model, \( n \) the sample size, and \( p \) the number of regressors including the intercept. A lower value for BIC indicates a better fit for the model (Montogomery et al., p.336).

Lastly, the F-statistic can be used to test the null hypothesis that all coefficients are zero (Montogomery et al., p.85).

### 3.4 Theory for Event Study

The methodology described here is taken from Kothari & Warner (2007). Note that the term beta that is used here and in subsequent chapters is not a general coefficient estimate but a specific finance term measuring how an individual security follows the overall market. The first step is to obtain the benchmark model and the abnormal returns (AR) for each security, for each day in the event window. Adding these individual abnormal returns generates the cumulative abnormal return (CAR) for each security. Lastly these CAR values are averaged to obtain the cumulative average abnormal return of the sample (CAAR).

To filter out events due to normal circumstances and obtain the abnormal return the market model is used as a benchmark. The model is defined as:

\[ r_{it} = \alpha_i + \beta_i r_{mkt} + \varepsilon_{it}, \quad i = 1,2,\ldots,n \quad (20) \]
Where, $r_{it}$ corresponds to the expected return of the $i$th security at time $t$ in the event window with the event occurring at $t=0$. $r_{mkt}$ is the notation for the market return (based on Nasdaq Stockholm). $\alpha_i$ (alpha) and $\beta_i$ (the beta) are standard coefficient from a standard OLS-regression with $\varepsilon_{it}$ as the error term.

Now the abnormal return is equal to the difference in the actual return of the time period and the expected return from the above model.

$$AR_{it} = r_{it} - (\alpha_i + \beta_i r_{mkt}) \quad (21)$$

Finally the CAR and CAAR equations are for the event window beginning at $t_1$ and ending at $t_2$:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t=t_2} AR_{it}, \quad (22)$$
$$CAAR = \frac{1}{n} \sum_{i=1}^{n} CAR_i(t_1, t_2) \quad (23),$$
4. Explorative Data Analysis

In accordance with previous research on the impact of divestitures on the stock price (Cusatis et al., 1993; Schipper and Smith, 1983), this thesis will use the Cumulative Abnormal Return (CAR) to measure the success of a divestiture in the short-term and as response variable.

4.1 Data Collection

Since the corporations being studied are publicity listed on Nasdaq Stockholm all data is freely available online. Inspired by the data collection of previous theses in the field of divestitures I have collected data on all spinoffs and equity carve-outs conducted on the Swedish stock exchange for a big enough time span to get a sufficient data set. This means looking at divestitures made by Swedish corporation between 2005 and 2018.

In this period there are some extreme events such as the financial crisis of 2008. Normally one should avoid these types of disruptive events but at the suggestion of Mattias Hamberg, professor at Uppsala university, using more than 10 years of data was required to collect a big enough data set.

Since this study is based around the announcement date, for a divestiture to be included, there must be a press release available or other formal information from a company that conclusively says which date is the announcement date. In the case this information was not available the divestiture was removed from the study. All of the financial metrics are collected from the annual report on the year before the announcement date, thus ensuring that the announcement does not bias the financial metrics. To investigate the refocusing hypothesis every press release is thoroughly examined to find any mention of the deal being made because of need to “focus on core activities”. In the end I have 31 divestitures that will be studied.

4.2 Variable Description

In this section the types of divestitures studied and the divestiture process is explained in detail. Furthermore, a mathematical description of the variable that will be used as the response variable in the regression analysis is presented.
4.2.1 Equity Carve Out vs Spin-Off

Two general methods a company can use to divest a subsidiary are spin-offs and equity-carve outs (Investopedia 2018). In a spin-off, the parent company distributes shares of the subsidiary that is being spun-off to its existing shareholders, typically receiving no cash in return. The subsidiary that has been spun off is a distinct entity with its own management. In an equity-carve out on the other hand the company sells some or all of its ownership in the company to the public in an initial public offering. Therefore, unlike in a spin-off the parent company receives a cash inflow form the transaction. There are other forms of divestitures structures such as split-offs but in this thesis only equity-carve outs and spin-offs will be evaluated where the company is listed on a stock-exchange.

4.2.2 Abnormal Return and the Market Model

In this thesis the success of a divestiture is measure by the abnormal return it generates in the short-term.

To determine the expected return that is subtracted from the actual return to yield the abnormal return there are several choices available. The mean adjusted return (MAR) has been used to study divestitures (Miles and Rosefeld, 1983). Another example is market-adjusted returns model (MKADJ) (Alexander et al., 1984). An advantage with the MAR model is that it minimizes the bias in the expected returns that arises with the market model because of the small size effect. (Levis, 1989; Dimson and Marsh, 1986). Still, in this thesis the market model is used. The motivation for this is that it is a very common approach used in many previous research articles (Montgomery et al., 1984; Jain 1985; Klein 1986; Brown et al., 1994).

4.2.3 Announcement Date and the Divestiture Process

The announcement date is the date that the divestiture is first announced but not yet confirmed and is thus the date from which the performance is measured in this thesis. After this first announcement, an extra board meeting is set up where board members will vote to confirm or reject the deal proposed by management. If the deal is voted through another press release is written that should not be confused with the initial release. A common occurrence is that the name of the new entity being formed is not determined at the time of this first
announcement, which complicates the collection of the data. The next step in the divestiture process for the company is to present the market with a prospectus with a more detailed background and motivation for the divestiture. As described in earlier, this information is not used in this thesis.

The motivation for using the announcement date rather than the date at which the divestiture is confirmed by the board is that studies have found no significant impact on the returns by the increased certainty associated with a completion announcement, compared to the statement of intention to divest that we call announcement date (Lasfer et al., 1996).

4.2.4 Return on Assets (ROA) and Return on Equity (ROE)

Return on assets measures the return on total company assets that go to all investors. Compared to the return on equity that corresponds to the return that goes to only equity holders. The formula for these two financial metrics are:

\[ ROA = \frac{Net \ income}{Total \ Assets}, \quad (24) \]

\[ ROE = \frac{Net \ income}{Shareholders'equity}, \quad (25) \]

4.2.5 Equity Ratio (leverage)

The Equity ratio is a good indicator of the level of leverage used by a company. It measures the proportion of the total assets that are financed by equity holders.

\[ Equity \ Ratio = \frac{Shareholders'equity}{Total \ Assets}, \quad (26) \]

4.3 Statistical methods

The mathematical framework in this thesis consists of an event study where the CAR is estimated to be used as the response variable in the second part of the results.

4.3.1 Event Study

The event study is conducted with the market model. This means that the CAPM is used to evaluate the “abnormal return” that measures the “success” of the divestiture. The index to calculate expected returns is Nasdaq OMX 30. Using this to calculate beta has its
disadvantages because it only tracks the 30 biggest companies on the Swedish stock exchange but because they are proportionally such a big part of the entire stock exchange, I believe it is reasonable to measure beta for a smaller company with this index. The preferred OMX PIL is a relatively new index and so did not have data available for all of the data. The data is selected as a 280-day trading day window, 30 trading days prior to the announcement. There are certain exceptions, where the original press release was published at the close of market, thereby the decision was made to use the next trading day as the de facto announcement date.

4.3.2 Regression Analysis

There are five main independent variables investigated in this thesis and the model fit will be evaluated with the forward selection and the "all possible regression" approach. Multicollinearity will be tested with pair-wise correlations and VIF. As described, all these variables are taken from previous research except the last two industry dummies that were introduced for this thesis specifically. A model with all variables looks like this for the $i$th transaction and event window $t$:

$$CAR_{it} = \beta_0 + \beta_{ROE} * x_{ROE} + \beta_{lev} * x_{lev} + \beta_{foc} * x_{foc} + \beta_{logMarketcap} * x_{logMarketcap} + \epsilon_i$$

$CAR_{it}$: The Cumulative abnormal return generated from the divestiture announcement

$x_{ROE}$: Return on equity, measures the firm profitability

$x_{lev}$: Measures the leverage of the company by equity ratio. Following the example of previous research this control variables used as a proxy for financial distress.

$x_{logMarketcap}$: Natural logarithm of firm’s market capitalization, which measures the size of the company.

$x_{foc}$: A dummy variable, indicating if the press release explicitly states the motivation begin the divestiture was to focus on core assets.

$x_{ROA}$: Measures the profitability to all shareholders.

$x_{med}$ & $x_{ind}$: Two extra dummy variables used separately indicating in which industry the parent company belongs, either healthcare (med) or industrials (ind).
To perform variable selection, I use BIC and $R^2$. The residual sum of squares is avoided because a problem with the residual sum of squares is that the measure always decreases as you add variables. So, by looking to reduce the RSS we almost always end up with the model with the most covariates.

### 4.4 Limitations in the Data

The main limitation of the data is that I have personally collected it. This gives room for potential bias introduced due to measurement error. Having studied previous student thesis in this area, I found they had misstated the correct announcement date in some cases and subsequently measured the abnormal return on the wrong event window.

Furthermore, as previously mentioned in the scope, due to the limitations in the data, some factors that would have been of interest cannot be studied since only the information in the initial press release is considered. An example is the financing hypothesis (Lang et al., 1995) that says that a company uses the proceeds form a divestiture to pay back its own debt will be rewarded by the market and the motivation of the divestiture is to obtain cheap financing. I found that Swedish companies do not tend to explicitly say that the intend to repay debt when announcing a divestiture in the initial press release, even if such a reason can be found in the prospect that is made available to the market after the board has made the final decision. I still aim to use the equity ratio of a parent company at the time of the divestiture to factor in capital structure, but this will be a proxy at best to the true hypothesis.
5. Results

The results consist of two parts. Firstly, estimated beta values used to calculate the abnormal returns are presented and then subsequently the CAR for each event. Secondly, the abnormal returns from Part I are used in the regression analysis in Part II.

5.1 Results Part I

5.1.1 Beta Values

The estimated beta values from the market model that are used to calculate the expected values are presented in table 5.1.1. These Beta values are estimated with OLS based on the market-model presented in equation (20) in section 3.4. The betas estimated individually with simple regression modelling were all significant. I use only one beta value for Lundin Petroleum because the estimates were similar in all three divestitures involving them.

Table 5.1.1
Beta values calculated for each security based on the market model. All coefficient estimations were found to be significant with $p = 0.01$ in each simple linear regression.

<table>
<thead>
<tr>
<th>Parent Company</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Addtech</td>
<td>0.48</td>
</tr>
<tr>
<td>NCC</td>
<td>0.76</td>
</tr>
<tr>
<td>Lundin Petroleum</td>
<td>1.02</td>
</tr>
<tr>
<td>Getinge</td>
<td>0.90</td>
</tr>
<tr>
<td>SCA</td>
<td>0.64</td>
</tr>
<tr>
<td>MTG</td>
<td>1.10</td>
</tr>
<tr>
<td>Addtech</td>
<td>0.47</td>
</tr>
<tr>
<td>Hemfosa</td>
<td>0.47</td>
</tr>
<tr>
<td>Autoliv</td>
<td>0.71</td>
</tr>
<tr>
<td>Xintela</td>
<td>0.71</td>
</tr>
<tr>
<td>B&amp;B Tools</td>
<td>0.54</td>
</tr>
<tr>
<td>XANO</td>
<td>0.58</td>
</tr>
<tr>
<td>Atlas Copco</td>
<td>1.2</td>
</tr>
<tr>
<td>Poolia</td>
<td>0.93</td>
</tr>
<tr>
<td>Kindred</td>
<td>0.24</td>
</tr>
<tr>
<td>Haldex</td>
<td>1.3</td>
</tr>
<tr>
<td>Brighter</td>
<td>0.55</td>
</tr>
<tr>
<td>BioGaia</td>
<td>0.69</td>
</tr>
<tr>
<td>Diginotana</td>
<td>0.46</td>
</tr>
<tr>
<td>IAR Systems Group</td>
<td>0.44</td>
</tr>
<tr>
<td>NGEx</td>
<td>0.46</td>
</tr>
</tbody>
</table>
5.1.2 CAR Values

The abnormal returns estimated are presented in table 5.1.2 with the event window [-1,0]. Which corresponds to the announcement day and the previous day, this event window was chosen to capture any effect from possible leaks prior to the announcement. For most of the divestitures, the CAR was positive and the CAAR was 0.38 %.

Table 5.1.2
Estimated Announcement cumulative abnormal returns are seen for each company in the data set. Summary data are presented also, showing a positive CAAR. Although it is not tested for significance.

<table>
<thead>
<tr>
<th>Parent company</th>
<th>CAR [-1,0] (%)</th>
<th>Parent company</th>
<th>CAR [-1,0] (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Getinge</td>
<td>0,02365</td>
<td>Brighter</td>
<td>0,004</td>
</tr>
<tr>
<td>SCA</td>
<td>0,04075</td>
<td>BioGaia</td>
<td>-0,0547</td>
</tr>
<tr>
<td>NCC</td>
<td>-0,03255</td>
<td>Dignitana</td>
<td>0,067</td>
</tr>
<tr>
<td>MTG</td>
<td>-0,0076</td>
<td>IAR Systems Group</td>
<td>0,0139</td>
</tr>
<tr>
<td>Addtech</td>
<td>0,0116</td>
<td>Lundin Petroleum</td>
<td>0,0092</td>
</tr>
<tr>
<td>Lundin Petroleum</td>
<td>0,0108</td>
<td>NGex</td>
<td>-0,0357</td>
</tr>
<tr>
<td>Hemfosa</td>
<td>0,007</td>
<td>DistIT</td>
<td>0,0413</td>
</tr>
<tr>
<td>Autoliv</td>
<td>0,0478</td>
<td>Vitrolife</td>
<td>-0,0086</td>
</tr>
<tr>
<td>Atlas Copco</td>
<td>-0,0115</td>
<td>Hexagon</td>
<td>0,039</td>
</tr>
<tr>
<td>Xintela</td>
<td>0,0359</td>
<td>RNB</td>
<td>-0,0448</td>
</tr>
<tr>
<td>Bergman &amp; Beving</td>
<td>0,0273</td>
<td>PEAB</td>
<td>-0,015</td>
</tr>
<tr>
<td>Xano</td>
<td>-0,0081</td>
<td>Bilia AB</td>
<td>0,0352</td>
</tr>
<tr>
<td>Poolia</td>
<td>0,0059</td>
<td>Fabege</td>
<td>-0,0185</td>
</tr>
<tr>
<td>Kindred/Unibet</td>
<td>0,0075</td>
<td>Betsson</td>
<td>0,1041</td>
</tr>
<tr>
<td>Haldex</td>
<td>0,0041</td>
<td>Lundin Petroleum</td>
<td>-0,0859</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Securitas</td>
<td>0,0097</td>
</tr>
</tbody>
</table>

Observations: 31
CAAR: 0,003795
Max: 0,1041
Min: -0,0859
5.2 Results Part II Multiple Linear Regression

In this section, I evaluate some of the hypothesis that I have constructed based on existing literature that might explain the abnormal returns estimated in part I. In the last section I test two industry dummies that I introduced, they are not based on previous research. First, all calculations leading up to the final model is presented, beginning with residual diagnostics.

5.2.1 Results for Residual Diagnostics

I study the studentized residuals on the full model with all covariates. The residuals should be randomly distributed around the horizontal line representing a residual error of zero. Looking at Figure 5.2.1 I see a fairly random pattern around –2 to 2. Naturally, with this little data it is difficult to say anything with certainty. There does not seem to be any clear outliers, considering the few data points to begin with, I avoid removing any points.

Figure 5.2.1 Studentized residual plot.

As explained in Section 3.2.3 a way to see if the errors are normally distributed is by studying the QQ-plot in figure 5.2.2, the residuals are not a terrible fit with regards to normality even though there seems to be a lighter tail for the residuals due to the “S-shape”.
In Figure 5.2.3 on the next page, the partial regression analysis is presented. Most graphs seem to have a positive slope indicating that they could have some impact on divestiture gains except for ROA which has a negative slope and Equity ratio and Log Market which have close to zero slopes indicating no contribution.
Figure 5.2.3 Partial regression on all five main covariates. All have a fairly clear slope except equity ratio and log market cap (Log_MK) which are close to zero. The clear slope of the others indicate that they could have some explanatory effect.
5.2.2 Results for Influential Observation

The first measure of influential points used is Cook’s distance. Looking at figure 5.2.4 one can see it returns the second data point as possibly influential.

Figure 5.2.4 Cooks-distance where the second data point seems to be influential.

Looking at the COVRATIO, Using the cutoff of 1.6 calculated by equation (10) in section 3.2.2 \(1 + \frac{3p}{n} = 1 + \frac{3 \times 6}{31} \approx 1.6\) it can be seen in Table 5.2.1 that the second point again indicates being an influential observation since the value 10.36 is above 1.5. Although as mentioned in section 3.2.2, the COVRATIO is preferably used on a large data set and 31 observations is small.

Table 5.2.1 COVRATIO

Using the cutoff of 1.6 we find again the second point drastically exceeding the limit as it did with the cooks-ratio.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.3139234</td>
<td>10.3612021</td>
<td>1.3586668</td>
<td>1.4607719</td>
<td>1.5557978</td>
<td>2.0369056</td>
<td>1.4809137</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
<td>13</td>
<td>14</td>
</tr>
<tr>
<td>3</td>
<td>0.6936993</td>
<td>1.9128435</td>
<td>2.2826238</td>
<td>1.4062588</td>
<td>1.4663858</td>
<td>1.5669626</td>
<td>1.5254252</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>18</td>
<td>20</td>
<td>21</td>
<td>22</td>
</tr>
<tr>
<td>5</td>
<td>1.5515060</td>
<td>1.5025730</td>
<td>0.8581818</td>
<td>1.5480344</td>
<td>1.5637746</td>
<td>0.8462676</td>
<td>1.2877400</td>
</tr>
<tr>
<td>6</td>
<td>23</td>
<td>24</td>
<td>27</td>
<td>28</td>
<td>29</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1.4529399</td>
<td>1.5239663</td>
<td>1.0417875</td>
<td>1.3763835</td>
<td>0.4130156</td>
<td>0.4511548</td>
<td></td>
</tr>
</tbody>
</table>

Deciding to remove the second point as an influential point seems to improve our model. The second data point corresponds to SCA divesting its hygiene units. It is possible
that there was some activity around the announcement date for SCA that severely biased this
data point. One explanation could be that the divestiture of its hygienic business unit had been
rumored for a long time.

The QQ-Plot with the influential point removed now looks slightly better in figure
5.2.5, The BIC-value also decreases from -84.17 to -109.82. So I am satisfied having removed
this influential point.

**Figure 5.2.5** QQ-Plot after removal of influential point

*The QQ-plot for the residuals has slightly improved after removing the data point for SCA.*

In table 5.2.2, the multiple linear regression can be seen for the full model with five
regressors. With all regressors I find significance for the estimated coefficients of ROA with a
negative coefficient, stating that investors reward parent companies who are not as profitable
as others contradicting hypothesis 3. However, ROE gives significance at a lower level but
interestingly has a positive coefficient, indicating that higher ROE for the parent company is
rewarded when divesting as suggested by hypothesis 4. But the size of the estimated
coefficient is much smaller and the p-value is higher.

Moreover, there is significance for the estimated coefficient focus, indicating that a
company explicitly mentioning the need to focus on core capabilities as reason for divestiture
leads to positive gains, thereby proving hypothesis 5.
**Table 5.2.2**

*Cross-sectional regression analysis on all covariates with the CAR as response variable. VIF tables are presented in the next section. Standard errors are in parenthesis.*

<table>
<thead>
<tr>
<th></th>
<th>CAR (-1,0) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus</td>
<td>1,93E-02*</td>
</tr>
<tr>
<td></td>
<td>(0,01095)</td>
</tr>
<tr>
<td>ROA</td>
<td>-0,1132**</td>
</tr>
<tr>
<td></td>
<td>(0,042514)</td>
</tr>
<tr>
<td>ROE</td>
<td>0,05822*</td>
</tr>
<tr>
<td></td>
<td>(3,18E-02)</td>
</tr>
<tr>
<td>Log Market CAP</td>
<td>-8,33E-05</td>
</tr>
<tr>
<td></td>
<td>(0,008253)</td>
</tr>
<tr>
<td>Equity Ratio</td>
<td>-0,009207</td>
</tr>
<tr>
<td></td>
<td>(3,22E-02)</td>
</tr>
<tr>
<td>Intercept</td>
<td>1,822e-03</td>
</tr>
<tr>
<td></td>
<td>(8,852E-02)</td>
</tr>
<tr>
<td>Observations</td>
<td>30</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0,1783</td>
</tr>
<tr>
<td>BIC</td>
<td>-109,82</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>2,258**</td>
</tr>
<tr>
<td></td>
<td>(df = 5; 24)</td>
</tr>
</tbody>
</table>

*Note:*  
*p<0.1  
**p<0.05
5.2.3 Multicollinearity Diagnostics

In this subsection the multicollinearity is assessed. In table 5.2.3, the pair-wise correlations are shown. It seems reasonable that there is some correlation between the variables. Looking at financial distress it stands to reason that smaller companies are often more likely to be in financial distress than larger companies and so there is a correlation between the logarithmic market cap and equity ratio. Moreover, since companies in certain industries are known to have a more leveraged capital structure than others, it is reasonable with a correlation between equity ratio and industry. To draw any conclusions on multicollinearity the VIF values are inspected next.

Table 5.2.3 Correlation Between independent variables

In this table the correlation between the independent variables is seen, including dummies for industry (Industrials and Healthcare). This table is part of an analysis of the multicollinearity since multicollinearity can be indicated by high correlation between the independent variables. It is no surprise that ROE and ROA are highly correlated. The healthcare industry is positively correlated with equity ratio which is no surprise because it is an industry known to carry low leverage. The log market cap has a high correlation with three of the other variables which could indicate multicollinearity. Other than that, most variables are fairly small. We will further investigate multicollinearity with VIF.

<table>
<thead>
<tr>
<th></th>
<th>Focus</th>
<th>ROA</th>
<th>ROE Equityratio</th>
<th>Log_MK</th>
<th>MED</th>
<th>IND</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus</td>
<td>1.00000000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROA</td>
<td>-0.17586752</td>
<td>1.00000000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROE</td>
<td>0.02699767</td>
<td>0.5361863</td>
<td>1.00000000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equityratio</td>
<td>-0.01820752</td>
<td>-0.18820373</td>
<td>0.07325220</td>
<td>1.00000000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log_MK</td>
<td>0.04904601</td>
<td>0.5326415</td>
<td>0.44180345</td>
<td>-0.46872164</td>
<td>1.00000000</td>
<td></td>
</tr>
<tr>
<td>MED</td>
<td>0.22173979</td>
<td>-0.3016519</td>
<td>-0.22017365</td>
<td>0.42192157</td>
<td>-0.22586208</td>
<td>1.00000000</td>
</tr>
<tr>
<td>IND</td>
<td>0.11643635</td>
<td>0.1049126</td>
<td>0.04747660</td>
<td>-0.0455329</td>
<td>0.2380402</td>
<td>-0.2148345</td>
</tr>
</tbody>
</table>

To further evaluate the multicollinearity I investigate the Variation inflation factors seen in Table 5.2.4. Even though the logarithmic market cap had high pair-wise correlation with the others I conclude that multicollinearity is not an issue due to the low VIF values across the board with no value exceeding 10 which was described as a cutoff in section 3.2.1.

Table 5.2.4
VIF values for the full model. No value is above 10.

<table>
<thead>
<tr>
<th></th>
<th>Focus</th>
<th>ROE</th>
<th>ROA</th>
<th>Equityratio</th>
<th>Log_MK</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIF</td>
<td>1.05</td>
<td>5.21</td>
<td>4.65</td>
<td>1.44</td>
<td>1.94</td>
</tr>
</tbody>
</table>
5.2.4 Results for Transformation

Trying to improve the model, I use a transformation. Because the abnormal returns consist of negative values, a log-transform is not possible. The result for the Box-Cox transform with power 1.5 is presented in table 5.2.5. The transformation did not improve the model.

<table>
<thead>
<tr>
<th></th>
<th>CAR (-1,0) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus</td>
<td>6,01E-04</td>
</tr>
<tr>
<td></td>
<td>(0,0023084)</td>
</tr>
<tr>
<td>ROA</td>
<td>-0,0099665*</td>
</tr>
<tr>
<td></td>
<td>(0,0055531)</td>
</tr>
<tr>
<td>ROE</td>
<td>0,0014208</td>
</tr>
<tr>
<td></td>
<td>(0,002076)</td>
</tr>
<tr>
<td>Equity Ratio</td>
<td>1,82E-03</td>
</tr>
<tr>
<td></td>
<td>(0,0064699)</td>
</tr>
<tr>
<td>LOG Market Cap</td>
<td>0,0009098</td>
</tr>
<tr>
<td></td>
<td>(1,66E-03)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0,0062560</td>
</tr>
<tr>
<td></td>
<td>(1,79E-02)</td>
</tr>
<tr>
<td>Observations</td>
<td>30</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>-0,03025</td>
</tr>
<tr>
<td>BIC</td>
<td>-144,0517</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>0,884</td>
</tr>
<tr>
<td></td>
<td>(df = 5; 14)</td>
</tr>
</tbody>
</table>

Note: *p<0,1  **p<0,05
5.2.5 Final model

I obtain the final model in two ways, first by forward selection and then by the all possible regression-method. Beginning with the Forward selection, the models are tried in the order seen in Table 5.2.6.

**Table 5.2.6** Forward selection
*In the forward selection, the test begins with only ROA as independent variable and then add one at a time. (1) corresponds to the intercept always being included*

<table>
<thead>
<tr>
<th>Focus</th>
<th>ROA</th>
<th>ROE</th>
<th>Equityratio</th>
<th>Log_MK</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In the below figure 5.2.6 the BIC-statistics is shown for the models beginning with ROA as sole independent variable. The black and greys indicate which independent variables are included and best fit is seen at the top of the figure with three covariates. I conclude that the best model fit is given by ROE, ROA and Focus included, while logarithmic market cap and equity ratio are not.

**Figure 5.2.6** BIC statistics for cross-sectional regression. *The colors show which variable sis included in the model for each respective BIC-value*
The resulting model with Forward Selection approach with only three covariates can be seen in table 5.2.7. The conclusions for the estimated values and significance are the same for the effect of Focus, ROA and ROE as in the full model.

Table 5.2.7 Final model with three covariates

*Multiple linear regression analysis on three covariates with the CAR (-1,0) as response variable. Standard errors are in parenthesis.

<table>
<thead>
<tr>
<th>CAR (-1,0) (%)</th>
<th>Focus</th>
<th>ROA</th>
<th>ROE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0,019594*</td>
<td>-0,109465**</td>
<td>0,056238*</td>
</tr>
<tr>
<td></td>
<td>(0,010452)</td>
<td>(0,042514)</td>
<td>(0,030005)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Intercept</th>
<th>Observations</th>
<th>Adjusted R^2</th>
<th>BIC</th>
<th>F-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0,003665</td>
<td>30</td>
<td>0,2382</td>
<td>-116,4935</td>
<td>4,022**</td>
</tr>
<tr>
<td></td>
<td>(0,007788)</td>
<td></td>
<td></td>
<td>(df = 3; 26)</td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0,1  
**p<0,05

Using the all possible regression method all $2^5$ models are tried. The lowest BIC value is -116,5 corresponding to the same model as above in the forward selection. In figure 5.2.7 three different figures are shown with $R^2$, adjusted $R^2$ and BIC all showing the best values for three variables. Since the all possible regression method gave the same result I use the model in Table 5.2.7 as my final model. The VIF values for Focus, ROA and ROE are shown in table 5.2.8.

Table 5.2.8 VIF Values for reduced model

*The VIF values are all below 10 and therefore it can be concluded that multicollinearity is not of concern.*

<table>
<thead>
<tr>
<th></th>
<th>Focus</th>
<th>ROE</th>
<th>ROA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1,03</td>
<td>4,49</td>
<td>4,48</td>
</tr>
</tbody>
</table>
Figure 5.2.7 All Possible Regression
There are three different figures. With the values for the criterions on the y-axis and number of covariates on the x-axis. One shows $R^2$ values (upper left), the other shows Adjusted $R^2$ (lower left) and the last shows BIC values (SBC) (upper right). They all indicate using three variables. The same variables selected with the Forward Selection approach above.
5.2.6 Regression Analysis with Industry Dummies

An additional test was made on two dummy variables indicating the industries Industrials and Healthcare. In table 5.2.9 it shows a negative coefficient for a company in the medicine industry but no explanatory power. The industry dummy has a positive coefficient and a lower p-value but still not significant.

It can be concluded that these two industry dummies cannot explain the divestiture gains in this data set.

Table 5.2.9 Multiple linear regression analysis with the introduction of dummy variable for companies in the healthcare industry (MED) and industrials (IND). Standard errors are in parenthesis.

<table>
<thead>
<tr>
<th></th>
<th>CAR (-1, 0) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus</td>
<td>1,64E-02</td>
</tr>
<tr>
<td></td>
<td>(0,011468)</td>
</tr>
<tr>
<td>ROA</td>
<td>-0,042418*</td>
</tr>
<tr>
<td></td>
<td>(0,02386)</td>
</tr>
<tr>
<td>IND</td>
<td>1,76E-02</td>
</tr>
<tr>
<td></td>
<td>(0,014169)</td>
</tr>
<tr>
<td>MED</td>
<td>0,001969</td>
</tr>
<tr>
<td></td>
<td>(1,60E-02)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0,008595</td>
</tr>
<tr>
<td></td>
<td>(8,53E-03)</td>
</tr>
<tr>
<td>Observations</td>
<td>30</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>0,154</td>
</tr>
<tr>
<td>BIC</td>
<td>-111,1262</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>2,32*</td>
</tr>
<tr>
<td></td>
<td>(df = 4; 25)</td>
</tr>
</tbody>
</table>

Note: *p<0,1
      **p<0,05
6. Analysis

First of all, the model fit was overall bad with low adjusted $R^2$ for the final model. Using 5 covariates with around 30 data points, might be too much to give any good models. Furthermore, there are tens of other possible explanatory variables that could explain the abnormal return from a divestiture. This thesis was only intended to test some of these factors and not fit an overall model to the CARs from the divestitures, so a bad overall model fit was expected.

To get 31 observations, I had to go back more than 10 years. It should be pointed out the possible bias introduced into the regression by including transactions around the financial crisis of 2008. Extreme events like that are difficult to compare to the status quo.

One factor that has been much documented in previous research is the Size Effect. Big companies are thought to be rewarded the most by divesting because the market sees the need to focus to be most pressing for large companies. This factor, that I quantified by logarithmic Market Cap, was the worst performing in this analysis. It had no explanatory power. One possible explanation for this is that many research papers have looked at the relative size instead of absolute values. That is; creating a dummy category called “large” if the Parent belonged to the 75th percentile of companies listed on the exchange that year. Because there was no access to a database where such historical data could be found for the author of this thesis, that was not explored. Naturally it is also possible that the size effect cannot be found in Sweden.

One significant factor that was found was profitability in the form of ROA. With lower ROA indicating higher CAR, going against hypothesis 3. A conclusion from this is that maybe it is not as lucrative for “healthy” companies as measured by profitability to divest as it is for non-“healthy” companies. It may seem contradictory with the ROE term signaling the opposite effect but because the estimated value was so small for ROE it is more reasonable to look at the negative effect of ROA which has higher significance. Moreover, perhaps this seemingly contradictory result comes from the stock market interpreting ROA and ROE differently. It may be that ROA is a better measure of financial health than ROE or vice versa.

The results for ROA go against the idea presented in section 2.4 on optimal portfolio management. A low ROA increased divestiture gains and not the other way around even though the idea from section 2.4 did align with my results for the ROE metric.
The fact that leverage measures by equity ratio and as a proxy for financial distress could not have an explanatory effect could then seem be counterintuitive to the claim that unhealthy companies are most rewarded. But this could be due to the market only rewarding non-healthy companies when it is measured by profitability and not when it is characterized by financial distress, it could also be that leverage-ratios are bad proxies for financial distress. As I analyzed the companies that are part of this data set, not a single company mentioned in their press release that they intended to pay down debt with the proceeds from the divestiture, indicating that perhaps none of them were in financial distress. Indeed, most of the companies have continued to be healthy companies today. A suggestion would be for future research to look further back in time to include companies especially during Swedish crisis in the middle of 90’s and early 00’s to find companies in financial distress.

Furthermore, as was brought up in section 2.3 the result of a divestiture can depend on whether the market interprets a divestiture from a company simply as a desperate need for cash or as a strategic value enhancer. The results from my study seem to indicate that the market did not interpret the divestiture from unprofitable companies as a sign of trouble and need for cash but a positive value enhancing tool.

A last point on the lack of findings for financial distress is that the mean adjusted model mentioned in section 4.2.2 has been found to be better than the market model to estimate CAR. This could further help explain the lack of findings in this regard.

The industry dummies did not have any explanatory power. The lack of significance is no surprise because I have too little data, the number of companies belonging to industrials was 6 and to healthcare only 5, and since they were variables I introduced myself and were not based on previous research.

The most important result in this thesis is the significance found for focus as a factor since research often mentions this as the most important. That is, companies that explicitly stated in their press release at the announcement date that the divestiture was being conducted due to a need to focus on core capabilities were rewarded more by the stock market than those that did not. The focus factor is also the one that features most predominantly in research on divestitures so this result aligns with global research. However, the significance level is only at p=0.1. A possible explanation is that using the dummy variable might not be the best case to represent the focus overall if you are looking at if focusing on core competencies is the key factor to divest. Some other research papers such as the student thesis by Dahlum and Tai use the number of business segments prior to the deal year and during the deal year to evaluate by
what percentage the total number of segments decreased, thereby getting a more specific look at focus. Another good variable they use is the strategic fit with the seller. They use SIC-codes from a database to determine if they are in the same segment or not. This last variable could not have been used in this thesis because there was not access to such a database.

Lastly, concerning the accuracy of these results. It must be stressed that only looking at 31 data points is bound to give uncertain results. I did not conduct a cross-validation to test if the results would only show up for this specific data. Furthermore, because this thesis was focused on the regression analysis, tests of significance with test statistics were not conducted on the CAR-values, as is custom in event studies, this is a weakness that impacts the results.
7. Conclusions

Swedish investors seem to reward companies that seek to divest to focus on core capabilities and those that are unprofitable, which in turn can be interpreted as the need to focus on core capabilities to become profitable. The first result aligns with research conducted in other countries. The ROA result does not align with previous research conducted from optimal portfolio strategy because the ROA coefficient estimate was negative although the positive estimate of ROE did support that theory but the estimated coefficient value was small and had lower significance. What is surprising however is that no significance could be found for the Size effect or for financial distress. This could possibly be because Swedish investors see these issues as different, or because of my sample size being too small for the size effect and because leverage is a bad proxy for financial distress.

7.1 Future Research

Since the sample is so small in Sweden it is difficult to be too sure on the results in my thesis and more detailed data needs to be looked at to properly evaluate what factors leads to the success of a divestiture.

Instead of looking only at Sweden, one should expand to all of the Nordics. That is the only way to get enough data to do a thorough regression analysis on all possible explanatory variables.

This thesis only looked at the effect in the short term over two days. Therefore it would be interesting to look at more long-term effects.

One last aspect that would have been interesting to look at is the effect of repeated transactions. How would the factor of “CEO-experience”, as an example, explain the success of a divestiture? In this data set there was only one company that conducted more than one divestiture during this time period so that was not a possibility.
8. References


**University Theses**


**Webpages:**


<https://corporatefinanceinstitute.com/resources/knowledge/deals/divesting/> 


9. Appendix

In this appendix a detailed description of the variables is presented as well as the full data set used in this regression analysis.

9.1 Control Variables

<table>
<thead>
<tr>
<th>Variable Type</th>
<th>Control Variable</th>
<th>Variable description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm Size</td>
<td>logMarketcap</td>
<td>Log transformed equity value of parent company</td>
</tr>
<tr>
<td>Financial Distress</td>
<td>lev</td>
<td>Equity ratio is used a proxy to indicate the financial distress of the company</td>
</tr>
<tr>
<td>Return on assets</td>
<td>ROA</td>
<td>A variable corresponding to profitability</td>
</tr>
<tr>
<td>Return on equity</td>
<td>ROE</td>
<td>Profitability to only equity shareholders</td>
</tr>
<tr>
<td>Focus</td>
<td>foc</td>
<td>Dummy variable, equal to one if the company has explicitly stated that the transaction is intended to enable the parent company to focus on core competencies</td>
</tr>
<tr>
<td>Industry</td>
<td>MED, IND</td>
<td>Two separate dummy variables indicating healthcare and industrials. In both cases equal to one if the company is in the respective industry.</td>
</tr>
</tbody>
</table>
### 9.2 Data Set

**Table 9.2.1** Parent company and divested company name with announcement date

<table>
<thead>
<tr>
<th>Parent Company</th>
<th>Divested Company</th>
<th>Announcement Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bilia</td>
<td>Catena</td>
<td>2005-06-22</td>
</tr>
<tr>
<td>Securitas</td>
<td>Loomis</td>
<td>2006-02-09</td>
</tr>
<tr>
<td>Peab</td>
<td>Peab Industrier</td>
<td>2006-10-09</td>
</tr>
<tr>
<td>Fabege</td>
<td>Klövern</td>
<td>2006-11-29</td>
</tr>
<tr>
<td>Betsson</td>
<td>Net Entertainment</td>
<td>2007-03-16</td>
</tr>
<tr>
<td>Hexagon</td>
<td>Hexpol</td>
<td>2007-06-11</td>
</tr>
<tr>
<td>RNB</td>
<td>Polarn &amp; Pyret</td>
<td>2007-10-19</td>
</tr>
<tr>
<td>Lundin Petroleum</td>
<td>Enquest</td>
<td>2010-04-10</td>
</tr>
<tr>
<td>MTG</td>
<td>CDON</td>
<td>2010-04-19</td>
</tr>
<tr>
<td>Haldex</td>
<td>Concentric</td>
<td>2010-07-16</td>
</tr>
<tr>
<td>Lundin Petroleum</td>
<td>Etrion Corporation</td>
<td>2010-10-05</td>
</tr>
<tr>
<td>I.A.R Systems group</td>
<td>Dist IT</td>
<td>2011-01-14</td>
</tr>
<tr>
<td>Pooilia</td>
<td>Dedicare</td>
<td>2011-04-07</td>
</tr>
<tr>
<td>Vitrolife</td>
<td>Xvivo Perfusion</td>
<td>2012-03-19</td>
</tr>
<tr>
<td>Dignitana</td>
<td>Braincool</td>
<td>2013-09-04</td>
</tr>
<tr>
<td>Xano Industri</td>
<td>AGES Industri</td>
<td>2014-04-08</td>
</tr>
<tr>
<td>Unibet/Kindred</td>
<td>Kambi</td>
<td>2014-04-11</td>
</tr>
<tr>
<td>Addtech</td>
<td>Addlife</td>
<td>2015-06-04</td>
</tr>
<tr>
<td>NCC</td>
<td>Bonava</td>
<td>2015-11-26</td>
</tr>
<tr>
<td>DISTIT</td>
<td>Alcadon</td>
<td>2015-12-21</td>
</tr>
<tr>
<td>BioGaia</td>
<td>Therapeutics</td>
<td>2016-02-12</td>
</tr>
<tr>
<td>Bergman &amp; Beving</td>
<td>Momentum</td>
<td>2016-05-11</td>
</tr>
<tr>
<td>NGEx</td>
<td>Filo Mining</td>
<td>2016-06-13</td>
</tr>
<tr>
<td>Getinge</td>
<td>Arjo</td>
<td>2016-10-18</td>
</tr>
<tr>
<td>Brighter</td>
<td>Camanio Care</td>
<td>2016-10-25</td>
</tr>
<tr>
<td>Atlas Copco</td>
<td>Epiroc</td>
<td>2017-01-16</td>
</tr>
<tr>
<td>Lundin Petroleum</td>
<td>IPC</td>
<td>2017-02-13</td>
</tr>
<tr>
<td>SCA</td>
<td>Essity</td>
<td>2017-04-05</td>
</tr>
<tr>
<td>Autoliv</td>
<td>Electronics</td>
<td>2017-09-14</td>
</tr>
<tr>
<td>Hemfosa</td>
<td>Nyfosa</td>
<td>2017-11-07</td>
</tr>
<tr>
<td>Xintela</td>
<td>Onkologiverksamhet</td>
<td>2018-03-20</td>
</tr>
</tbody>
</table>