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FUNDAMENTAL IMPACT
An Empirical Analysis of the Relationship Between Fundamental Value Drivers and Four Commonly Applied Multiples in the E&P and Telecom Industries

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ABSTRACT

This thesis conducts an empirical analysis of the relationship between fundamental value drivers and multiples in two industries with different economic characteristics; namely, the telecommunication and oil exploration and production industries. By conducting quarterly linear regressions on 1,324 unique companies, in two different industries, and on four commonly applied valuation multiples on data from 1980 to 2019, the results of over 1,000 linear regressions are thoroughly analyzed and interpreted from a statistical and economic perspective. The empirical analysis revealed that most of the theoretically expected relationships between the fundamental value drivers and multiples examined in the linear regressions were ambiguous. The findings of this thesis suggest that prevailing external factors, incorporation of future prospects, and additional characteristics of contemporary finance may explain the detachment of market valuations from fundamentals.
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1 Introduction

A company’s value is determined by the supply and demand for the company’s shares - representing the equity share of the company assets, and the market value of debt - representing the liability share of the company assets. As the cash flow from debt is mostly agreed upon when the company issues securities at some form of a pre-determined interest rate, the market value of equity is more challenging to estimate. The market value of equity depends on the value that can be claimed by the shareholders, which is highly dependent on the company’s future performance. There are several different models for calculating the value of a company, and some models are more appropriate than others, depending on the company or industry characteristics. Using the fundamental value approach, the value is a function of a subjective assessment of future performance likely based on historical accounting figures. Since there are differences in practices, and investors have different views of the companies’ future projections, there is inconsistency in valuations creating a market for trading the companies’ shares. Hence, the companies’ share price represents the markets’ consensus value.

Different industries have unique characteristics; hence, investors have different views of what they consider to be important indicators for setting the right valuation. As the valuation models are partly based on the financial statements, there are a set of metrics that are used to evaluate four critical aspects that impact the assessment of the value, namely profitability, growth, and risk. These factors are substantial when estimating the value, and breaking them further down will provide metrics that are frequently discussed when comparing companies.

As each industry have their unique characteristics, some metrics are considered more suitable and important than others within industries. Take the oil industry and the telecom industry as examples: The oil industry is characterized as cyclical and the companies are extracting a generic product that is resold to the market, controlled by supply and demand. The product is consumed and distributed globally, some actors have substantially more control than others, and is frequently used as a political instrument in international politics. This creates volatile pricing, and thus volatile valuations for the companies that have a high level of direct exposure to the oil price. A telecom company, on the other hand, does not extract any product that they resell. They invest in infrastructure that can provide people with communication services. This industry has seen high growth as technology has evolved, and is dependent on yielding a good return on their services.
Hence, investors that attempt to find equities that can yield good future returns may prefer different indicators when trying to choose the right investment due to the differences in the industry characteristics.

A company’s fundamentals are, therefore, hugely important to consider when one is estimating the value of a company. Investors want to estimate the value as accurate as possible, in order to calculate the risk and potential return on the investment. Investors are constantly developing strategies to chase returns, where finding the right indicators for value drivers and the ability to assess new information quickly are critical aspects. The financial markets have developed greatly over the last decades and understanding the evolvement of how investors think and behave are important in order to invest successfully.

2 Research Topic

The complex nature of valuations therefore brings us to the research topic of this thesis. We seek to uncover the disputed relationships that exist between accounting fundamentals - represented by an assorted set of value driving metrics, and the valuation of companies - represented by valuation multiples. Not only do we seek to understand the current relationship, but we also intend to study how the relationship has evolved over time and how they find themselves relevant in regards to historical events. We have chosen to investigate two industries with different economic characteristics in order to see if the importance of these fundamentals has had a different impact in the respective industries. In short, we seek to answer the following research question:

Research Question

"To what degree do fundamental value drivers affect the market value of companies within the E&P and telecommunication industry, which indicators are considered important, and how has the relationship evolved over time?"

A literature review will be disclosed to set the context of the research topic and to review theories that are relevant in order to provide a better understanding of how this thesis will contribute to existing literature. We will later present the theoretical framework we will apply in our quest to answer the research question. The valuation theory is a crucial component of this thesis as we break down the multiples into intrinsic multiples, which is at the core of the analysis. As the analysis is based on large data sets, the linear regression theory is of vital importance to understand the
assessments and selections we do along the way. This is to ensure that the underlying assumptions are met to the best degree possible, and that the analysis results are properly interpreted.

As we later will argue, we use relative valuation multiples and accounting measures rather than absolute values for more efficient inclusion of companies across all sizes and operating currencies. The theoretical derivation and breakdown of the multiples will set the frame for which accounting variables we choose to extract and how we construct the database. Hence, the theoretical relationship will set the base for the first hypothesis:

Hypothesis 1

"The fundamental value drivers impact the multiples as proposed by theory."

After calculating the relevant metrics we will perform a descriptive analysis to get an overview of each fundamental value driver and the relationship between them and the relevant multiple. This will better help us structure the analysis and provide indications of interesting relationships that we can study more closely in the analysis. We will do this by finding the median values of the fundamental value drivers and multiples each quarter, which will then be graphed against each other in order to evaluate the development of the variables over time. Based on the findings from the descriptive analysis we further revise more specific hypothesis.

Hypothesis 2

"The relationship between fundamental value drivers and the multiples are unstable across time."

Hypothesis 3

"There is a positive relationship between the oil price and the multiples in the E&P industry."

To test the hypotheses, we are performing quarterly and pooled linear regression analysis with all the identified value drivers for each of the multiples assuming they are not violating the underlying assumptions. The linear regression models will be analyzed in-depth in order to confirm or reject the hypotheses, and will hopefully provide us with a greater insight into the relationship between fundamentals and valuation.

The models will then further be refined in an attempt to optimize the model. Variables will hence be included or excluded based on the underlying assumptions, economic and statistical significance
and the explanatory power. We will then use the results to perform a valuation to test how the refined linear regression models value companies compared to the more applied industry median approach.

**Hypothesis 4**

*The refined linear regression models yield more economically reasonable estimates of value than the median industry multiples.*

To test this hypothesis, we will use the output from the model to perform a valuation on two selected companies. If the refined linear regression models provide adequate results, we will successfully have created a set of models for four commonly applied multiples that can serve as an alternative to the most-used median multiple approaches. All the hypothesis will be discussed throughout the paper, and partial conclusions will be given along the way. Lastly, the findings of this thesis will be discussed and a final conclusion to the research question will be provided. As a final remark, we will also disclose the suggestions to future research of this thesis’ topic. Hence, the paper will be structured as follows:

![Figure 1: Structure of Thesis](image)
2.1 Delimitation

Due to the desire for an in-depth analysis of fundamentals in industries with a specific set of characteristics, we have chosen to delimit this thesis to focus on the oil exploration and production and telecommunication industries. In order to gather a diversified and valid data sample and produce pragmatic models comparable to those used in business practices, we have chosen to delimit the valuation multiples to some of the most used and well-known. Hence, the P/B, P/E, EV/EBITDA, and EV/Sales multiples have been chosen to represent the valuation multiples and dependent variables.

Furthermore, the fundamental measures, represented by the derived value drivers, will be limited to those derived from theory for the quarterly and pooled linear regressions. However, for the refined linear regression models we will include industry-specific and macroeconomic variables that we consider interesting based on the descriptive analysis. Lastly, the available accounting and valuation data naturally limit the time frame of the analysis for each multiple and thus can vary across the multiples. The quarters that did not have what we considered as a sufficient amount of observations were excluded from the analysis to ensure valid and reliable results.

Moreover, the models are based on the theoretical framework of linear regression, implying that the analyzed data should have a linear relationship in order to yield reliable results. Non-linear data may be reshaped to meet the model requirements. We find this method most appropriate in investigating the relationship between the company fundamentals and market valuation, as we can perform a set of tests to ensure that the results and the model assumptions are both valid and reliable. The nature of the framework applied allow us to analyze the economic and statistical significance of both the underlying fundamentals’ impact on the dependent variable, as well as the statistical significance and explanatory power of the overall models. Other statistical methods could have been applied; however, the approach we have chosen is in line with the methods that are applied in the related research that will be disclosed in the next section.
3 Literature Review

There are little literature written that are aiming to map out fundamental value drivers’ effect on valuation multiples. Damodaran (2012a) is one of few that examined the relationship between fundamental value drivers and multiples, building upon the earlier work of Kisor and Whitbeck (1963). In these studies, they use dividend payout ratio, firm beta, and earnings growth as independent variables and potential determinants for the firms price to earnings ratio. Yearly linear regressions run on data from 1987 to 1991 exhibited fluctuating coefficients and declining explanatory power over time. The later regressions from 2000 to 2011 yield more reliable results due to more data available and the findings indicate earnings growth as a good insight into how the market is valuing growth. In line with expectations, the earnings growth multiple peaked around the 2000s’, implying that the market paid more for expected growth during the dot-com bubble than later in the following financial crisis where the coefficients were lower. The study concludes that “Firms with higher growth, lower risk, and higher payout ratios, with other things remaining equal, should trade at much higher multiples of earnings than other firms. To the extent that there are differences in fundamentals across countries, across time and companies, the multiples will also be different.” (Damodaran, 2012a). In the study, Damodaran (2012a) appreciates the convenient way of compressing large amounts of data into a single equation that captures the relationship between the multiple and the financial fundamentals, but emphasis that the conflicting signs could be a consequence of some multicollinearity present in his data. Furthermore, he emphasizes that the regression is based on the linear relationship between multiples and fundamentals, which might not be appropriate as an analysis of the residuals may suggest a logarithmic or squared transformation of the dependent variables.

Acosta-Calzado, Acosta-Calzoda, and Murrieta-Romo (2010) criticize the commonly used industry average multiple approach for relative valuation, and introduces the ”REVAAM model”. They argue that applying the industry average multiple for valuation fail to adjust for fundamental differences among comparable companies, even though they operate within the same industry. They use linear regressions to estimate an adjusted P/E and EV/EBITDA multiple by accounting for profitability factors such as return on equity, net earnings margin, return on capital and tax operating margin. They use logarithmically transformed multiples and examine U.S. company data in the period between 2000 and 2009. Their results show declining explanatory power and low coefficient values, yet significant F-tests implying an adequate significant model. The model was also
found useful to assess whether an industry was over- or undervalued by using the linear regression parameters to compare the simple average industry multiple to the multiples estimated based on average industry fundamentals. Overall, the study succeeds in displaying a positive relationship between profitability measures and earnings multiples and presents a convenient model. However, the research fails to discuss assumptions regarding multicollinearity and heteroscedasticity which could cause unreliable results.

A comprehensive study conducted by Ali (2014) aims to construct a model that can perform a valuation of any fully listed company in the S&P 500, FTSE-All-Share and STOXX Europe 600 indices, using a cross-sectional relative multiple regressive approach on firm data between 2001 and 2011. The thesis thoroughly analyzes the relationship between multiples such as price to book, earnings, sales and EBITDA, and a list of independent proxy variables covering growth, risk, margin, payout ratios, size, ROE, and macroeconomic proxies. The analysis indicates that earnings measures are prone to volatility, impairing the suitability of bottom-line figures as overall projectors. However, the outcome from the regressions display significant explanatory power and results that all reflect significant findings that there is an increase in the confidence of the predictive ability of the financial model attributes, enabling estimation of company value (Ali, 2014).

3.1 Industry-Specific Literature

The literature disclosed above all analyze the relationship between fundamental value drivers and commonly used valuation multiples to some extent. However, they all cover fairly broad markets segments and neglect to examine the industry-specific differences properly. In order to get a deeper understanding of which proxies that drives the multiples in the telecommunication and oil exploration and production industry, it deems appropriate to present literature that is more specific to the industries we will investigate in this thesis.

A team from PwC covering the telecommunication industry recognized that executives were increasingly frustrated because while meeting the expectations of investors and analysts, they were not achieving the EBITDA multiples they expected. Intending to identify the new drivers of EBITDA multiples in the telecom industry, they find that growth, which earlier has been the surest route to premium multiples, is no longer favorable as many markets start to reach their capacity. The analysis displays little to no correlation between EBITDA-, margin- and cash flow growth to multiples valued at a premium. The key metric that seemingly drives valuation premiums according to
their report is the return on capital, as the industry is capital intensive and slowly shifting towards ex-growth (Sur, Meakin, Taylor and Russell, 2014). Except from disclosing data comprising of 71 firms worldwide and a timeline of ROI from 2004 to 2013, the report provides little specifics regarding the analysis’ methodology and data sample.

A collaborative research paper of representatives from University of Stavanger and Statoil ASA (Equinor) suggests that return on average capital employed (ROACE) is a predominant indicator for the oil industry, based on assumptions regarding the correlation between rentability and valuation metrics. Undertaking regression analysis on market and accounting data from 11 oil companies between 1997 and 2002, they test the Enterprise Value-to-Debt Adjusted Cash Flow (EV/DACF) multiple against several financial indicators. Their findings do not support the perceived positive relation between ROACE and market-based cash flow multiples. The linear regression yields strongly significant effects regarding company size and oil price. Hence, a simplified valuation model that only includes annual dummies representing the oil price and another set of dummies accounting for size and reputation proves to have a substantial explanatory power (Osmundsen, Asche, Misund and Mohn, 2006). The paper takes inspiration from earlier work of Chua and Woodward (1994), performing a regression analysis to test the price to earnings figures for integrated oil companies against beta, interest rate, financial leverage, asset turnover, profit margin, and dividend payout ratio. As the study fails to find support for the hypothesis they swap P/E as the dependent variable with share price, as well as adding cash flow from operations and proven reserves as independent variables. The analysis accentuates future cash flow and reserves as significant explanatory factors, supporting a fundamental approach to the valuation of oil companies.

3.2 Contribution to Literature

In the previous sections, we disclosed literature we deemed relevant for the thesis. All of the research does to some extent study the relationship between fundamental value drivers and valuation multiples or other similar metrics. However, many of these papers mainly focus on estimating value based on fundamentals, adjusting multiples based on fundamentals or are looking into a specific fundamental-multiple relationship. In addition, our impression is that some research fails to ensure data quality (and quantity) through properly assessing assumptions, adjusting the data for these, and adequately disclose research methodology.
In this thesis, we will analyze how the effect of fundamental value drivers have evolved over time. By running quarterly linear regressions on 1,324 unique companies in two different industries, on four selected valuation multiples on data from 1980 to 2019, the results of over 1,000 linear regressions are thoroughly analyzed and interpreted. With this vast set of data, we obtain numerous and precise data points, enabling us to better capture the evolution of the importance of the different metrics over time and uncover relationships between valuation multiples and value driving proxies. Also, we will run a cross-sectional pooled linear regression on each of the multiples, as well as creating a set of refined linear regression models in an attempt to provide greater insights into other potential value driving metrics outside what is proposed by theory.

Fundamental metrics should be essential to a company’s valuation as it contains information about a company’s ability to grow, generate profit, and risk profile to mention a few. In the cyclical industry of E&P, companies are extracting a commodity in which they sell to the next step in the value chain, consequently making them reliant on the price of their product. In contradiction, telecommunication companies mainly sell service and are therefore not particularly reliant on the value of an external asset. We have found no prior research attempting to uncover whether the fundamental metrics will be of greater importance in industries characterized as such. With this paper’s scrutiny, we will contribute to the existing literature by covering a multitude of fundamental value drivers’ effect on a broader specter of valuation multiples, carefully analyzing evolution of industry characteristics and fundamentals over time. In addition, we will make use of the results to create a simple model for valuation purposes.

4 Linear Regression Theory

4.1 Linear Regression Models

Yan and Gang Su (2009) stated that linear regression analysis was the first of the regression analysis to be researched rigorously and broadly applied by practitioners, and is today the most widely used tool of all statistical techniques and has reached a pivot point in econometrics when analyzing the interactions among two or more variables. By using linear regression analysis, some of the possible regression objectives include predicting future observations, assessing the relationship between two or more variables and a general description of data structure. Hence, this is a powerful tool on our quest to understand the interplay between fundamentals and market values and to build appropriate valuation models.
The objective of the linear regression model is to examine which variables the dependent variables rely on. The multiple linear regression model attempts to model the relationship between two or more independent variables and a dependent variable by fitting a linear equation to the observed data. Similarly, a simple linear regression model with a single independent variable enables us to see how well each variable can explain the dependent variable. The linear regression model is defined as:

\[ Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \epsilon_i \]  

(1)

As seen above, \( Y_i \) represents the dependent variable, \( \beta_0 \) denotes the intercept, \( \beta_k \) is the slope of the chosen independent variable \( X_k \), and lastly, the error term \( \epsilon_i \) indicates the variation in \( Y_i \) that is not estimated by the linear relationship. The equation has the property that the prediction for the dependent variable is a straight-line function of each of the independent variables, holding the other independent variables fixed, and the contributions of the independent variables are constants and additive. However, as the residuals of the linear regression model are random variables, it is crucial to determine whether the error term is correlated to the independent variables when formulating a linear regression model as it can alter the slope coefficients (Seal, 1967). Moreover, the linear relationship between the dependent variable and independent variables may also be seen as somewhat restrictive. However, Faraway (2002) emphasizes that the linear regression model is actually very flexible, as the variables can be combined and transformed (squared, natural logs, etc.) in any way and thus accommodate for non-linear relationships. Additionally, he underpins that truly non-linear models are rarely necessary, and often emerge from a theory about the relationships between the variables rather than empirical analysis.

### 4.1.1 Ordinary Least Squares (OLS)

Lai, Robbins, and Wei (1978) stated that the ordinary least squares (OLS) are the simplest and most common estimator due to its conceptually and computationally simple nature. The OLS estimator minimizes the sum of squared residuals, which is the error term that arises because of variation between the actual and predictive dependent variable. The unknown parameter \( \beta \) is thus estimated with the closed-form expression described below:

\[ \hat{\beta} = (X^TX)^{-1}X^TY \] 

(2)

The Gauss-Markov theorem states that in a linear regression model in which the errors have expectation zero, are uncorrelated and have equal variances, the best linear unbiased estimator
(BLUE) of the coefficients is given by the OLS estimator, provided it exists. In this context, best means giving the lowest variance of the estimate as compared to other unbiased, linear estimators. Moreover, the OLS estimator is unbiased and consistent if the residuals have a finite variance and are uncorrelated with the independent variables. The OLS estimator is also efficient under the assumption that the errors have a finite variance and are homoscedastic, meaning that the conditional error term does not depend on the sequence of the independent variables. Hence, under these assumptions and given the Gauss-Markov theorem, we know that the OLS estimator is unbiased and have minimum-variance among all unbiased linear estimators (Gujarati and Porter, 2009).

4.2 Linear Regression Assumptions and Remedies

The main four assumptions behind the linear regression model are linearity and additivity of the relationship between the dependent and independent variables, normality of the error distribution, statistical independence of the errors, and constant variance of the errors. In multiple linear regression models, we also assess the level of multicollinearity between the independent variables. A violation of any of these assumptions could make the linear regression model inefficient, severely biased or misleading.

4.2.1 Linearity

The first assumption states that there must be a linear and additive relationship between the dependent and independent variables. This implies that the expected value of the dependent variable is a straight-line function of each independent variable when holding the others fixed, the slope does not depend on the values of the other variables, and the effects of the different independent variables on the expected value are additive. Contrary, the relationship may be exponential or even multiplicative, which would require a transformation of the respective variables.

The assumption is tested using a plot of observed versus predicted values, and the linearity assumption is obtained when the observed values are symmetrically distributed around the predicted regression line (Nau, 2017).

4.2.2 Homoscedasticity

The second assumption states that the errors have to be homoscedastic, implying a constant variance of the errors. If the errors are heteroscedastic, equivalent to a non-constant variance of the
errors, the violations of the assumption can cause the standard deviations to be inconsistent and thus the calculation of the p-values more insecure (Newbold et al., 2013). Heteroscedasticity can also yield confidence intervals that are too wide or too narrow, especially when the variance of the errors is increasing over time, as well as it may have the effect of giving too much weight to small parts of the sample – typically where the error variance is largest – when estimating the linear regression coefficients (Nau, 2017). In order to test for homoscedasticity, we evaluate plots of residuals versus predicted values as well as we apply the White test, which allows the independent variables to have a non-linear and interactive effect on the error variance. The null hypothesis states that the error variance is constant and homoscedastic. If the null hypothesis is rejected, it implies that the errors are heteroscedastic and subject to non-constant variance.

4.2.3 Normality

The third assumption states that the error terms are normally distributed. If the residuals in the error term are not normally distributed, it can create problems for determining whether the coefficients of the model are significantly different from zero as well as estimating confidence intervals for forecasts. Typically, the error distribution will also be skewed by the presence of a few large outliers (Nau, 2017).

In order to test for normality in the error terms, we assess normal probability plots of the residuals as well as we apply the Shapiro-Wilk test. The normal probability plots are plots of the fractiles of the error distribution versus the fractiles of a normal distribution having the same mean and variance (Nau, 2017). The Shapiro-Wilk test tests the null hypothesis that the error terms are normally distributed. If the null hypothesis is rejected in favor of the alternative hypothesis, the error distribution can be characterized as non-normal (Torres-Reyna, 2007).

4.2.4 Independence of Residuals

The fourth assumption states that the errors have to be statistical independent of each other, which implies that there is no correlation between the error terms (Newbold et al., 2013). In a linear regression model, independence of residuals can be violated if the errors tend to always have the same sign under particular conditions, for instance, if the model systematically underpredicts or overpredicts what will happen when the independent variables have a particular structure (Nau, 2017).
In order to investigate the independence of the residuals, the residuals are plotted against the row numbers to assess whether there appears to be any form of systematic under- or overpredictions. We also apply the Durbin-Watson test, where the null hypothesis states that the residuals are independent of each other. The consequence of correlation between the residuals is that the OLS estimator is not the optimal estimator as it underestimates the real value of the variance of the residuals. Hence, the estimates of the OLS estimation will be unbiased, but inefficient.

4.2.5 Multicollinearity

Multicollinearity is present in a multiple linear regression model when there is a close to perfect linear relationship between some or all of the independent variables. This implies that two or more independent variables are highly correlated (Newbold et al., 2013). A consequence of multicollinearity is high standard errors causing the estimates to change unevenly in response to small changes in the model or data.

In order to test for multicollinearity, the Variance Inflation Factor (VIF) has been applied. VIF tells us how much larger the standard error is compared to what it would have been if the variable had zero correlation with the other independent variables. This implies that the more the VIF increases, the less reliable the regression results will be. We have chosen to set the VIF-limit equal to 10, which is in line with Bowerman et al. (2005).

4.3 Model Evaluation

The linear regression models will generate several statistical measures explaining the dataset which will be considered in order to evaluate the quality and how well the linear regression models serve our purposes related to the hypotheses. Gujarati (2004) describes three central concepts in that sense, which will be outlined in the following sections.

4.3.1 Hypothesis Testing

The objective behind tests of significance is to use sample results to verify the truth or falsity of a null hypothesis, and thus test whether the estimated coefficient $\beta_k$ has any linear influence or explanatory power on the dependent variable. Hence, we test whether $\beta_k$ is significantly different from zero. By assuming that $\mu_i \sim N(0, \sigma^2)$ we can use the t-test to test the hypothesis about any
individual partial regression coefficient. The t-test is defined as:

\[ t = \frac{\hat{\beta}_j - \beta^0_j}{SE(\hat{\beta}_j)} \]  

(3)

With \( n - k \) degrees of freedom, we can use the t-test to determine the p-value of the coefficient. The p-value of the linear model indicates the reliability of the independent variable to predict the dependent variable. We reject the null hypothesis in favor of the alternative hypothesis if the p-value is less than, or equal to, the chosen significance level. Contrary, if the p-value is higher than the chosen significance level, the null hypothesis is not rejected.

In order to test the joint hypothesis that the regression coefficients are different from zero simultaneously, we apply the analysis of variance (ANOVA), and the F-test defined as below:

\[ F = \frac{ESS/(k - 1)}{RSS/(n - k)} \]  

(4)

The p-value for the F-test is computed with \((k - 1)\) degrees of freedom in the numerator and \((n - k)\) degrees of freedom in the denominator. By using the same interpretation as for the t-test, the regression coefficients are jointly significantly different from zero if the p-value is less than, or equal to, the chosen significance level.

4.3.2 The \( R^2 \) Criterion

The \( R^2 \) is the proportion of variance in the dependent variable that is predictable from the independent variables. A higher \( R^2 \) indicates a more accurate linear regression model, and the criterion takes a value between 0 and 1. The \( R^2 \) is computed as follows:

\[ R^2 = \frac{ESS(Explained \ Sum \ of \ Squares)}{TSS(Total \ Sum \ of \ Squares)} = 1 - \frac{RSS(Residual \ Sum \ of \ Squares)}{TSS} \]  

(5)

However, in the assessment of the multiple linear regression models, we apply the adjusted \( R^2 \) to determine the explanatory power of the linear models and for comparative purposes. Gujarati (2004) explains that the \( R^2 \) criterion has several issues related to out-of-sample forecasts, linear model comparisons, and the fact the criterion will always increase as more variables are added to the linear model. Accordingly, the adjusted \( R^2 \) is a modified version of the \( R^2 \), which has been adjusted for the number of independent variables in the model.

\[ \bar{R}^2 = 1 - \frac{RSS/(n - k - 1)}{TSS/(n - 1)} = 1 - (1 - R^2) \frac{n - 1}{n - k} \]  

(6)

The adjusted \( R^2 \) only increases if the new term improves the linear model more than would be expected by chance, which implies that the absolute t-value of the added independent variable is greater than 1. As seen by the notation, the value will always be equal to or less than the \( R^2 \).
4.3.3 Akaike Information Criterion

Lastly, the Akaike Information Criterion (AIC) is penalizing the inclusion of independent variables even further, and is computed as below:

\[
\ln AIC = \frac{2k}{n} + \ln \left( \frac{RSS}{n} \right) \tag{7}
\]

The \(2k/n\) is the penalty factor, where \(k\) is the number of independent variables (including the intercept) and \(n\) is the number of observations. AIC is useful when comparing two or more linear regression models, and the linear model with the lowest value is preferred. The AIC criterion is also very applicable for out-of-sample forecasting.

5 Valuation Theory

5.1 Introduction to Valuation

To value assets and companies, practitioners need to have a good understanding of how an asset or business works, how it adds value, and how it returns value to investors (Penman, 2013). Value is a particularly helpful measure of performance, as it takes into account the long-term interests of all the stakeholders in a company, not just the shareholders (Koller et al., 2010). Thus, knowledge of how companies are creating value and how practitioners measure value is an essential intellectual equipment in the market economy.

Companies create value by investing capital they raise from investors to generate future cash flows at rates of return exceeding the cost of capital, referred to as excess returns. Furthermore, companies can sustain strong growth and high returns on invested capital only if they have a well-defined competitive advantage. The excess returns are a result of the company’s competitive advantages or barriers to entry into the industry, and high excess returns locked in for a very long period implies that the company has a permanent competitive advantage (Damodaran, 2012a).

In the absence of any clear indication of the true value of stocks, investors cope in different ways. The intuitive investors rely on their instincts, the passive investors trust the market efficiency, whereas the fundamental investors examine the information and consequently reach conclusions about the underlying value that the information implies, recognized as the intrinsic value. The intrinsic value of a valuation is not a term of accuracy or the true objective value, and will always be biased by the practitioner’s perceptions. Moreover, the application of valuation models in
investment decisions is based upon a perception that the markets are inefficient and make mistakes in assessing value, as well as an assumption about how and when these inefficiencies will get corrected. In an efficient market, the market price is the best estimate of value, and therefore the purpose of all valuation models is the justification of the model’s estimated value (Damodaran, 2012c).

5.2 Fundamental Valuation

Practitioners use a wide range of models to value companies in practice, and the present value approach is the foundation on which all other valuation approaches relies on. The present value approach aims to estimate the intrinsic value of an asset based upon its fundamentals and values the asset by estimating the present value of all cash flows generated by the asset at the appropriate discount rate. In the following section, we will focus on explaining the several different valuation techniques used within the present value approach in order to be able to understand differences in value across different valuation models.

5.2.1 The Dividend Discount Model

The dividend discount model estimates the value of equity of a company by taking the present value of all future dividends, and in case of an infinite dividend stream and a constant discount factor, the dividend discount model is specified as:

$$MVE_t = \sum_{t=1}^{\infty} \frac{Dividend_t}{(1 + r^E)^t}$$

(8)

However, since the projection of dividends to infinity is almost impossible and time-consuming, as well as it does not tell a lot about value creation, a two-stage dividend discount model is often preferred:

$$MVE_t = \sum_{t=1}^{n} \frac{Dividend_t}{(1 + r^E)^t} + \frac{Dividend_{n+1}}{r^E - g} + \frac{1}{(1 + r^E)^n}$$

(9)

As seen above, this two-stage model divides the projection of future dividends into two periods; an explicit forecast period with individual growth rates, and a terminal period with a constant growth rate, also referred to as Gordon’s growth model. The key concept of this distinction is that the growth rate of a company will eventually approach the long-term growth rate of the economy in which the company operates, although the explicit forecast period deviates due to differences in lifecycles (Petersen and Plenborg, 2012).
5.2.1.1 Advantages and Disadvantages

The dividend discount model can be characterized as a simple valuation model, which is also quite intuitive for investors as dividends are something you get as a shareholder. Furthermore, the fact that the model is based on dividends is especially favorable for the explicit forecasting period, as dividends usually are quite stable in this time frame (Penman, 2013).

However, there are several flaws with the model that have to be addressed. First, as already touched upon, dividends do not reveal anything about how value is created and is simply a distribution of value created, a concept also referred to as the dividend conundrum (Penman, 2013). Second, dividend payouts are used by companies as an indication of positive future prospects, but it is not necessarily tied with profitability. Companies that do not pay out dividends, or have a meager payout ratio, can instead of paying out dividends invest their excess reserves into valuable, growth projects which will yield attractive returns in the future. By assuming these companies will pay out dividends when they reach maturity, forecasting such long-term payouts is challenging and will increase the uncertainty of the forecasts. Hence, the dividend discount model is not the most popular model among practitioners, but it serves as the basis for the other present value models and is thus theoretically equivalent since the estimated value yields identically across all present value models.

5.2.2 The Discounted Cash Flow Model

As opposed to the less favored dividend discount model, the discounted cash flow model is undoubtedly the most popular of the present value models and solves some of the issues outlined above as it focuses on the investing and operating activities of the firm, activities that do create value. By using the two-stage enterprise value approach, the discounted cash flow model estimates the enterprise value by taking the present value of future free cash flows, where the value of equity is obtained by subtracting the net interesting bearing debt from the enterprise value as expressed below:

\[
MVE_t = \sum_{t=1}^{n} \frac{FCFF_t}{(1 + WACC)^t} + \frac{FCFF_{n+1}}{WACC - g} \times \frac{1}{(1 + WACC)^n} - NIBD_t
\]  

Where:

\[
FCFF_t = EBIT_t \times (1 - t_c) + Depreciation & Amortization_t - \Delta NWC - CAPEX_t
\]
The free cash flow is obtained by subtracting the cash flow from investing activities from the cash flow from operations, and measures how much cash that is available to all investors, including equity- and debtholders, through the operations of the business after accounting for expenses of the business such as operating expenses and capital expenditures. The free cash flow to the firm also measures a company’s ability to generate excess cash, which can be invested in different value creating projects or programs. Consequently, a high or rising level of free cash flow is often signaling a company that is thriving in its current environment.

5.2.2.1 Advantages and Disadvantages

The discounted cash flow model appears as an attractive valuation approach since it forecasts operating activities which are sources of value creation, as well as free cash flows are considered to be a reliable measure that eliminates subjective accounting policies. Although the model forecasts the value creation part of the business, it also penalizes companies that invest heavily. As investing activities do not create value in the short run, the model demands a long forecast horizon in order to capture the value of these investments, which increases the uncertainty of the estimate (Penman, 2013). Hence, the model is quite applicable when practitioners are confident regarding future free cash flows, but it is also susceptible to the underlying assumptions, and even small adjustments can cause the intrinsic value to vary widely and thus not be an accurate measure.

5.2.3 The Residual Income Model

One of the disadvantages of the two previously introduced models is that they both require long forecasting periods in order to capture all the value, which decreases the reliability of the estimated intrinsic value. Penman (2013) states that a valuation technique anchored on what we know and value in the near future should be favored over a valuation technique that recognizes most of the value far out in the infinite future. One model that has gained increased attention in recent years is the residual income model, which acknowledges Penman’s (2013) statement as it is based on the company’s current book value. The model relies on accrual accounting data as opposed to the previous models that rely on cash flow data, and estimates the value of equity of a company based on three terms; the current book value of equity, the present value of residual income in the forecast horizon, and the present value of residual income in the terminal period (Petersen and Plenborg, 2012).

\[
MVE_t = BVE_t + \sum_{t=1}^{n} \frac{RI_t}{(1 + rE)^t} + \frac{RI_{n+1}}{rE - g} * \frac{1}{(1 + rE)^n}
\]  

(11)
Where:

\[ RI_t = (ROE_t - r^E) \times BV_{E_{t-1}} \]

The model rests on the assumption that the estimated value of equity can only be above the book value of equity if the present value of the expected residual incomes is positive, and below if vice versa. As seen from the breakdown of residual income, the formula underpins the significance of return on equity and book value of equity as drivers of the residual income, and it becomes obvious that the estimated value of equity exceeds the book value of equity only when returns exceed the cost of equity capital.

5.2.3.1 Advantages and Disadvantages

As the residual income model is based on accrual accounting data, it matches value added to the value given up and identifies value ahead of cash flows, which implies that the model does not penalize the company for its investing activities. The fact that the model is anchored on value already recognized in the balance sheet, the properties of the model allow the forecasting horizon to be shorter than for the other presented models, and thus less dependent on speculation. The model is also very intuitive, and generate value estimates that appear easier to understand, as it is more focused around value creation and increase the awareness of value drivers. However, it relies on accounting numbers, which can be manipulated and thus should be used together with an accounting quality analysis (Penman, 2013).

5.2.4 The Abnormal Earnings Growth Model

Similarly to the residual income model, the abnormal earnings growth model focuses more on the immediate future than the distant future but relies on the valuation on current or forward earnings rather than the current book value of equity. The central concept of this model is earnings growth in excess of normal earnings - at the required rate of return - on prior earnings, also referred to as abnormal earnings growth. This can also be interpreted as that one does not pay for growth that comes from an investment that yields only the required return (Penman, 2013). Moreover, the earnings growth is based on cumulative earnings, which are the reported earnings as well as reinvested dividends, an idea that recognizes that earnings arise both from earnings earned by the asset, but also earnings earned from reinvesting dividends into other assets. Thus, the cumulative dividends are defined as below and subsequently compared to the normal earnings that are relative
to the prior earnings:

\[
\text{Cum. Div. Earnings}_t = \text{Earnings}_t + (\text{Required Return} \ast \text{Dividend}_{t-1})
\]

\[
\text{Normal Earnings}_t = (1 + \text{Required Return}) \ast \text{Earnings}_{t-1}
\]

The difference between the two equals the abnormal earnings growth (AEG), or alternatively expressed as a growth rate relative to the required rate of return:

\[
AEG_t = \text{Cum. Div. Earnings}_t - \text{Normal Earnings}_t
\]

If the abnormal earnings growth is positive, this is the growth we should pay for. The abnormal earnings growth model estimates the value of equity as the capitalized earnings plus the excess value of the abnormal growth using forward earnings:

\[
MVE_0 = \frac{\text{Earnings}_1}{r_E} + \frac{1}{r_E} \left[ \frac{AEG_2}{(1 + r_E)^2} + \frac{AEG_3}{(1 + r_E)^3} + \ldots + \frac{AEG_n}{(1 + r_E)^{n-1}} \right]
\]

Which is simplified to:

\[
MVE_0 = \frac{1}{r_E} \left[ \text{Earnings}_1 + \frac{AEG_2}{(1 + r_E)^2} + \frac{AEG_3}{(1 + r_E)^3} + \ldots + \frac{AEG_n}{(1 + r_E)^{n-1}} \right]
\]

The model can also estimate the value of equity using current earnings, and in such case, the value of equity is pre-dividend as the dividend does not reduce current earnings as with the forward earnings.

\[
MVE_0 + d_0 = \frac{1 + r_E}{r_E} \left[ \text{Earnings}_0 + \frac{AEG_1}{(1 + r_E)^1} + \frac{AEG_2}{(1 + r_E)^2} + \ldots + \frac{AEG_n}{(1 + r_E)^n} \right]
\]

### 5.2.4.1 Advantages and Disadvantages

The main advantage of the abnormal earnings growth model compared to the other valuation techniques is that it emphasizes on earnings and earnings growth, which are measures practitioners care and think a lot about, and aligns nicely with the perception of investors that value should be based on the earnings potential of the company (Penman, 2013). As the model relies on current or immediate future earnings, it also allows for a shorter forecast horizon like the residual income model. However, the model does not give as much insight into value creation as the residual income model and does not anchor on the book value of equity, which increases its sensitivity to subjective inputs and arbitrary factors.
5.2.5 Cost of Capital and Risk Factors

A common feature across all valuation models is the cost of capital, which is the required return providers of financing expect on their invested capital. The cost of capital depends on the risk involved in supplying funds to a firm and the time value of money (Petersen and Plenborg, 2012). The cost of capital can also be interpreted as the opportunity cost of foregoing an alternative investment with the same risk (Penman, 2013). There have been developed numerous approaches to estimate the cost of capital, and the following section will discuss both quantitative and qualitative approaches in order of doing so.

5.2.5.1 Cost of Equity

A risk-averse investor providing financing for the company wants to be compensated for bearing risks. The equity holders are the last to get paid in terms of bankruptcy, and thus carry a greater risk than other stakeholders and require a higher return as compensation for bearing higher risk. In that regard, the cost of equity is applied to estimate the owners’ required rate of return for investing in the company. The most common way of calculating the cost of equity is to use the Capital Asset Pricing Model (CAPM), and according to the CAPM the investors’ required rate of return is based on three factors; the risk-free rate, the equity beta and the market risk premium.

\[ r^E = r^f + \beta^E (r^M - r^f) \]  \hspace{1cm} (16)

The basic idea is that investors’ are able to diversify sufficiently to eliminate idiosyncratic risk, and the only risk an investor needs to bear and should be rewarded for is the level of systematic risk, measured in the equity beta. The higher the systematic risk, the more investors’ require in compensation for investing in the company. Technically, the equity beta measures the covariance between the returns on a specific stock and returns on the market portfolio divided by the variance of the market return.

5.2.5.2 Cost of Debt

The cost of debt refers to the required rate of return debt holders require for providing financing for the company. The cost of debt is expressed after-tax, as interest is tax deductible, and typically determined by the risk-free rate, the credit spread and the corporate tax rate (Petersen and Plenborg, 2012).

\[ r^D = (r^f + r^S) (1 - t_c) \]  \hspace{1cm} (17)
However, there are several ways to estimate the pre-tax cost of debt, and the most obvious approach is to use the firm’s outstanding long-term bonds and compute the yield on the bonds, whereas it is also possible to use credit rating estimated by credit agencies. Still, many companies do not have credit ratings or outstanding tradeable bonds, and in such cases, it is possible to examine the most recent borrowing history of the company to get an idea of what has been charged. Another approach is to use financial ratios and assign a synthetical credit rating based on an assessment of financial ratios of a rated firm, and compare it with the unrated firm’s corresponding ratios (Damodaran, 2012a).

5.2.5.3 Weighted Average Cost of Capital (WACC)

Companies raise cash from several sources, and the WACC expresses the minimum required rate of return that a company must achieve in order to satisfy its debt holders, equity holders and other providers of capital. The WACC is profoundly affected by the capital structure of the company and is determined by taking into account the relative weights of each component of the capital structure relative to the cost of equity and cost of debt after tax (Petersen and Plenborg, 2012).

\[
WACC = \frac{MVE}{EV} \times r^E + \frac{NIBD}{EV} \times r^D \times (1 - t_c)
\]  

When determining the cost of capital, the asset pricing model evaluates the riskiness of the company’s operations solely based on how the firm is financed and is not including the riskiness of the operations. We could argue that the operational risk of fundamentals such as dividend payouts, earnings or cash flows should be seen by the fluctuations in the stock price assuming an efficient market. However, if the market does not capture such fluctuations, the equity beta will remain unchanged or increase if the market has sliced the share price relative to the market based on irrational reasons, and thus provide an inadequate risk measure. As a consequence, Penman (2013) suggests that the perception of risk based on fundamentals is a more appropriate approach than using an asset pricing model due to market inefficiency.

5.2.5.4 Fundamental Risk Factors

Fundamental risk can be characterized as the risk that an investor bears as a result of the way a company conducts its activities. The fundamental risk approach suggested by Penman (2013) is divided into two parts; the risk from investing and operating activities referred to as operating risk, and the risk from financial activities referred to as financial risk. The two components are the basic fundamental determinants of equity risk and can be further decomposed into value drivers.
Rearranging the formula of the cost of capital, which is also referred to as the cost of operations, the cost of equity can be expressed as:

\[ r^E = WACC + \frac{NIBD}{MVE} \times (WACC - r^D) \tag{19} \]

As of above, the equation indicates that the cost of equity depends on the cost of operations, equivalent to the operating risk, and the market leverage multiplied by the spread between the cost of operations and cost of debt, equivalent to the financing risk. Thus, if the company is unlevered, the cost of equity equals the cost of operations and has a positive relationship with the level of leverage due to increased financial risk.

In the sense of the previously introduced valuation approaches, the key focus has been to estimate the value of equity, and thus it is shareholder value that is at risk. This can be exemplified by the residual income model, where shareholder value is driven by the expectation of future residual income, which again is driven by the return on equity and growth in book value of equity. Hence, the fundamental risk for an equity investor is determined by the possibility of not earning the forecasted return on equity, or not being able to grow their book value at the return on equity (Penman, 2013).

Penman (2013) explains the determinants of fundamental risk in figure 2 as how the risk of not earning the expected return on equity is determined by the risk of not earning the expected return on operations (OR₁), compounded by the risk of financial risk turning unfavorable (FR). The risk of not earning expected residual earnings is the ROE risk compounded by growth risk (OR₂).

Figure 2: Fundamental Risk Factors (Penman, 2013)
Operating Risk

In further detail, the return on equity is driven by the return on net operating assets (equivalent to the return on invested capital), financial leverage and the spread between the return on net operating assets and net borrowing cost. The first part determining the return on equity is the return on net operating assets, which expresses the overall profitability of operations. The variations in the operating returns can be explained by variations in the profit margins, asset turnovers and operating liability leverage, which are the key elements behind the operational return.

The profit margin risk is the risk that the profit margins will change for a given level of sales, and is determined by the expense risk and the operating leverage risk. The expense risk expresses the risk of expenses, such as labor and material costs, per dollar of sales, while the operating leverage impacts the fluctuations in profit margins caused by the relationship between the firm’s fixed and variable costs. The asset turnover risk identifies the possibility of falling sales due to decreased demand or increased competition and is determined by the velocity of the sales relative to the net operating assets. Last of the three key elements explaining the return on equity is the operating liability leverage risk, which is the risk of reduced operating liabilities in percentage of net operating assets. Reduced operating liability leverage implies that the firm is granted less credit, maybe as a consequence of less confidence from its financial providers, and this means the company has to take a bigger burden of the investments in operating assets, which increases the net operating assets and lowers the return (Penman, 2013).

Financing Risk

The second part of the return on equity explains the effect of financial leverage on the overall profitability. The spread between the return on net operating assets and net borrowing cost has a positive impact if positive, and a negative impact if negative. The financial leverage risk is the first part explaining the financing risk of the company and is estimated as the amount of net financial obligations relative to the common shareholder’s equity. Higher financial leverage increases the fluctuations on return on equity caused by the spread. The second part of the financing risk is the borrowing cost risk, which influences the spread. A company which depends heavily on the variable-interest-rate debt will have a higher borrowing cost risk than a company with fixed-interest-rate debt (Penman, 2013).
Growth Risk

Residual earnings are driven by both return on equity and growth risk in net operating assets, which implies that new investments that generate returns greater than the required rate of return add value to the company. Thus, the return on equity is compounded by the risk that the equity will not increase as expected, and as a consequence, bring uncertainty about whether the company can increase investments in net operating assets, which is an additional aspect of operating risk (Penman, 2013). The growth risk in net operating assets is determined by growth in sales since for a given asset turnover rate, the level of sales determines the amount of net operating assets required. Hence, growth risk is the risk that the sales are not growing as anticipated.

![Figure 3: Summary of Risk Factors](image)

5.3 Relative Valuation

As presented in the previous sections, the objective of the present value approach is to find the value of assets, given their cash flow, growth potential and risk characteristics. In relative valuation, the objective is to value assets, based upon how similar assets are currently priced in the market. An essential aspect for a potential investor is to investigate how similar companies are priced in the market relative to some performance measure before he or she makes an investment decision, and multiples indicate with ease whether a company is either over- or undervalued relative to its peers.

5.3.1 Standardized Values and Multiples

In order to ensure that the conclusions and investment decisions that are being made have consistent quality and are comparable across peers, market values have to be standardized in some way as a mature company with solid financials will look more expensive than a start-up within the same industry. This is where the multiples come in handy. The multiples scale the market value to a common variable, a variable that has a logical relationship to the observed market value and therefore can be seen as a driver of the market value. In other words, you compare how much the market is willing to pay for a unit of the common variable. By doing so, it is possible to compare market values across peers despite differences in business characteristics. Typically used common
variables are related to the revenues or earnings the companies generate, to the book value of the companies themselves, or industry-specific measures (Damodaran, 2012a).

5.3.2 Advantages and Disadvantages

Valuation based upon multiples is often popular among practitioners, as it is technically simple, an apparent low level of complexity and easy to perform. However, multiples are easy to use and easy to misuse and should be interpreted with care.

5.3.2.1 Advantages

There are several reasons why practitioners so widely use relative valuation. One of the main advantages of relative valuation is its simplicity. The approach uses simple accounting measures from the financial statements, as well as it is based on far fewer assumptions than a full fundamental analysis, and are thus far cheaper and quicker to conduct. The simplicity of the method enables practitioners to value a large sample of companies in relatively short time with negligible costs, as well as it makes it easier and more intuitive to present to clients and customers compared to present value analysis. Lastly, relative valuations are more likely to reflect the current mood of the market, since the valuations are based on how the market is pricing companies relative to its peers, and thus yield values that are closer to the market valuations than their intrinsic values (Damodaran, 2012a).

5.3.2.2 Disadvantages

The simplicity of using multiples in valuation is both an advantage and a disadvantage. As relative valuations rely on relative pricing of peers, inconsistent estimates of value can occur as comparable companies can still differ on risk, growth potential and cash flows, although the companies have the same business characteristics. Thus, a thorough valuation based on multiples is both quite complicated and time-consuming. Furthermore, the multiple approach only yields unbiased value estimates under very restrictive assumptions, and in reality only happen by chance as short cuts are often made when multiples are applied. In a perfect world, all companies used in the relative valuation should have the same economic characteristics and outlook, accounting policies and exclude transitory items (Petersen and Plenborg, 2012). The lack of transparency concerning the underlying assumptions in relative valuations make them particularly vulnerable to manipulation.
Lastly, as the relative valuations are more likely to reflect the current mood of the market, that also implies that the multiples may be too high when the market is overvaluing peers, or too low when the market is undervaluing these peers. For example, during the dot-com bubble of the late 90s, prices of tech companies were pushed by speculators to implausible heights justified by skyrocketed multiples of peers (Colombo, 2012). The experience of the late 90s showed that an entire sector could become detached from economic fundamentals when investors rely too heavily on relative valuations. Hence, despite the shortcomings, relative valuation is best applied as a supplement to the present value approach in order to obtain a more accurate forecast.

5.3.3 Applications

There is no doubt multiples are widely used by practitioners, and studies show that almost 85% of equity research reports on Wall Street are based upon multiples, as well as more than 50% of all acquisition valuations. Rules of thumb regarding investment decisions are not only common but the basis for final valuation judgments. In those cases where fundamental analysis has been conducted, the objective in many of these is to back into a number that has been obtained by using a multiple (Damodaran, 2012b).

Thus, pulling together a group of comparable peers is essential in order to obtain consistent estimates. A comparable company is one with cash flow, growth potential, and risk similar to the company being analyzed (Damodaran, 2012a). However, finding the right companies for the peer group is challenging, as industries are often loosely defined. Companies in the same industry with the same business characteristics are often called comparable, but that is not necessarily the case. One alternative approach to control for differences among peer group is to look for companies that are similar in terms of valuation fundamentals, and thus using key properties as selection criteria. Another approach is to construct linear regression models in order to justify why a company should be over- or undervalued relative to the typical firm in the industry (Damodaran, 2012a).

5.3.3.1 Subjective Adjustments

When practitioners conduct multiple analysis, they normally identify a peer group, compute the median multiple and accordingly compare the median multiple to the estimated multiple of the company to assess whether the company is over- or undervalued relative to its peers. However, practitioners may also use subjective adjustments in order to create a convincing story of why the company is priced as it is. By calculating key properties related to cash flow, growth potential,
and risk of the peer group, they may be able to justify the difference from the median multiple by differences in key properties. Still, if such properties cannot explain the difference, it is difficult to justify that the company should trade at a higher multiple than the median multiple of the industry.

5.3.3.2 Modified Multiples

Another approach used is to modify the multiple to take into account the most crucial variable determining it, such as the return on equity for the price to book value ratio, and then divide the multiple by the leading determinant for the multiple. The modified multiple implicit assumes that peer group is comparable on all other measures of value, other than the one being controlled for, and linearity between the multiple and the leading determinant is required (Damodaran, 2012a). As companies in peer group can still differ on various characteristics, the invoked assumptions of the approach are quite restrictive and may yield inconsistent estimates.

5.3.3.3 Linear Regression of Key Drivers on Multiples

Based on the remarks from the modified multiples section, it is possible to control for more than one dissimilarity among peer group by regressing several key value drivers on the relevant multiple. This linear regression approach works well if the dataset is sufficiently large and the relationship between the relevant multiple and key value drivers are fairly stable over time (Damodaran, 2012a). The linear regression will generate several measures indicating how well the independent variables explain the relevant multiple in terms of statistical and economic significance.

There are several advantages of choosing this approach compared to subjective comparisons across peer group (Damodaran, 2012a). First, the linear regression approach quantifies, based upon actual market data, the degree to which increased profitability, higher growth or risk should affect the multiples. Second, it is favorable in industries with relatively few companies, as you do not have to restrict your choice of peers to industry, but can include all firms in the market. The linear regression model controls for differences on key value drivers that the practitioner believes may affect the relevant multiple across firms. Lastly, it allows the practitioners to examine whether all companies in the peer group are over- or undervalued by inserting the company values for the independent variables into the regression equation, and subsequently the result can be directly compared to the median multiple.
5.3.4 Distributional Characteristics

Along with controlling for differences among peer group, it is also crucial to be aware of the distributional characteristics of the multiples. As the objective of the multiple analysis is to evaluate whether a company is over- or undervalued relative to its peers, practitioners have to be aware of the benchmark multiple as well as the highs and lows in the industry.

5.3.4.1 Average, Median, and Outliers

At first, we would expect the average value of the multiples to be the benchmark value of the peer group. A multiple can from a mathematical point of view obtain a negative value, although this does not make sense from an economic point of view, as it is not possible to pay less than zero for a company. Thus, since multiples can never be less than zero and are unconstrained in terms of maximum value, the distributions of these multiples are naturally skewed towards the positive values. Consequently, the average values of these multiples will be higher than the median values, as well as the sensitivity of outliers will result in averages that are not representative for peer group (Damodaran, 2012a). We therefore use the median value of the multiples as it provides a better indication of the typical firm in the industry.

5.4 Valuation of Cyclical Companies

The objective of the fundamental and relative valuation approach, despite the stated differences in estimation between the two, is to provide an estimate of the value of the company based on assumptions on how the company will act and perform in the future. While this is also the case for cyclical companies, the assessment of the future assumptions related to cyclical companies compared to non-cyclical companies are particularly challenging and requires modifications.

5.4.1 Earnings Throughout the Cycles

A cyclical company is one whose earnings and cash flows demonstrate a repeating pattern of significant increases and decreases (Koller et al., 2010). Their value is often more dependent on the movement of a macroeconomic variable or industry factor than it is on company-specific characteristics (Damodaran, 2009). Thus, their volatile earnings and cash flows are the primary origins of the valuation issues practitioners’ face valuing such companies.
As seen in the upper part of the figure, the non-cyclical firm with historically flat earnings is quite simple to forecast, as the level of future earnings can be predicted using the historical growth rate to increase the current earnings. The lower part of the figure shows the historical earnings of a cyclical company, and in contrast to the non-cyclical company, forecasting the level of future earnings is far more complicated. As the current earnings in figure 4 are at the bottom of the cycle, and the historical growth rate the last years has been negative, extrapolating the negative trend into the forecast will be an inaccurate forecast given the cyclicality. Thus, the valuation needs to take into account where the current earnings are in the current cycle, and this is what makes the valuation of cyclical companies so challenging.

5.4.2 The Market Valuation of Cyclical Stocks

As commodity prices and economics move in cycles, the biggest problem we face in valuing companies is that earnings and cash flows reported in the most recent year are a function of where we are in the cycle, and extrapolating those numbers into the future can result in serious misvaluations (Damodaran, 2009). Even though the practitioner knows where the current cycle is standing, the future cycle still has to be forecasted, and it will be entangled with the practitioner’s predictions about when the economy will turn and how strong the up- or downturn will be (Damodaran, 2012a).

Koller et al. (2010) investigate how the market is pricing cyclical companies, and find out that by assuming practitioners in the market were using the discounted cash flow approach to value cyclical companies with perfect foresight about the industry cycle, that the values of the model would exhibit much lower volatility than the earnings or cash flows of the companies. Hence, the share prices of the cyclical companies were much more volatile than the model would suggest, which
can be explained by investor bias of anchoring on current earnings when predicting the future. Koller et al. (2010) continue their investigations and examine practitioners earnings forecast for 36 cyclical companies over a 12 year period, and their results are fascinating. They discover that the consensus forecast is totally ignoring the cycle, and actually makes no attempt to predict it, and actually shows a continued upward trend no matter where the companies are in the cycle. Thus, this implies that investors who rely on consensus’ forecasts are implicitly basing the future on the current earnings, which can partly explain the volatility observed in the share price.

As Damodaran (2012a) pointed out, Koller et al. (2010) do not believe the market does not predict the cycles but acknowledge that an investor will never have perfect foresight of the industry cycle. Hence, they also include two new scenarios with a blend of perfect foresight and zero foresight. In the figure below, Koller et al. (2010) illustrate a four-year forecast of cyclical companies with three levels of foresight. As seen of the perfect foresight scenario of the industry cycle, the valuation is quite stable, as none of the single years’ earnings have a significant impact in the value of the company compared to the actual share price. The zero foresight scenario, where practitioners are anchoring on current performance and the current trend as the new long-term trend, shows massive fluctuations in the value estimate. This underpins that the practitioners assign too much value close to the peak and too little value at the bottom of the cycle. The last scenario mixes half and half the perfect foresight scenario and the zero foresight scenario, and this scenario is much closer to the actual share price than the other scenarios. Thus, this implies that the market tries to forecast the cycle based on past cycles, but also assigns some probability to the scenario where the company breaks out of the current trend and anchoring the forecast on the current performance.

Figure 5: Forecast of Market Values for Cyclical Companies with Three Levels of Foresight (Koller et al., 2010)
5.4.3 Multiples and Cyclical Companies

Similarly to the fundamental valuation approach, the multiples of cyclical companies will behave differently than the multiples of non-cyclical companies. In particular, the multiples will display much more volatility and thus fluctuate more during the cycle than a non-cyclical company. For instance, the price to earnings multiple tends to bottom out at the peak of the cycle and be at its highest at the bottom of the cycle (Damodaran, 2009). At the peak of the cycle, practitioners expect that a downturn is just around the corner, and accordingly assign a lower multiple due to modest growth outlooks. Contrary, the multiple will be at its most expensive at the bottom, since practitioners expect a coming up-turn and thus better growth outlooks.

Figure 6: Expected P/E Multiple Contraction and Expansion in Cyclical Stocks

The fact that the multiples are inversely related to the earnings cycle comes from the assumption that the earnings for a cyclical company fluctuate more and faster than the share price. However, this illustration is based on the assumption of perfect foresight, and as Koller et al. (2010) states, practitioners also focus on the current performance. Hence, practitioners will forecast higher earnings at the peak and lower earnings at the bottom, resulting in a higher valuation at the peak and a lower valuation at the bottom, which will most likely reduce the effect of the illustrated contraction and expansion pattern seen above.

5.4.4 Remedies for Cyclical Earnings

As explained, the share prices of cyclical companies appear too volatile to be consistent with the value estimates of the fundamental and relative valuation approach. As the current year is typically used as the base year and growth rates are used to project future earnings and cash flows, the current earnings may be too low or too high to use as a base year due to the current stage of the economic cycle. However, Damodaran (2012a) argues there are two potential remedies for cyclical earnings. The most commonly used approach to cope with volatile earnings over time is to normalize earnings. Normalizing earnings involves ignoring the economic cycle forecast and
instead concentrate on understanding what the company will earn in a normal year. A normal year is defined as a year where the earnings are neither depressed nor pushed up by the economic cycle, and thus reflect the mid-point of the cycle or where the commodity prices reflect the underlying equilibrium between supply and demand (Damodaran, 2009). Hence, by using the normal year as the base year for future projections, the forecast will lead to a more conservative forecast when the cycle is in a peak year and a more optimistic forecast when the cycle is at the bottom.

Figure 7: Normalization of Earnings for a Cyclical Company

The second approach is handling volatile earnings by adjusting the expected growth rate in the near periods to reflect the expected changes in the economic cycle, and thus allowing the earnings to follow the cycle in the short-run, and after that normalize earnings in the long-run (Damodaran, 2009). This approach requires the practitioner to forecast the near future, and the accuracy of the value estimate depends on the precision of the macroeconomic predictions, making it a compromise between normalizing earnings and forecasting the cycle.

Figure 8: Adaptive Growth and Normalization in the Long-Term

Moreover, Damodaran (2009) says that if the normalized environment can reflect what the company can earn in a normal year, there need to be some consistency in how the market is valuing companies
relative to their earnings. Hence, in the absence of differences in growth and risk across companies, the companies should trade at the same multiple of normalized earnings, and the only reason for differences in value is that some companies have brighter growth prospects or are less risky than the others. From a relative valuation perspective, normalized multiples will be more stable than multiples based on trailing or current earnings, but using unadjusted multiples may also serve a purpose in valuation as if the earnings for all companies in the industry move in line with the cycle (Damodaran, 2009).

6 Theoretical Multiple Drivers

As elaborated, the value of a company is a function of three variables; the company’s capacity to generate cash flows, its expected growth in these cash flows and the uncertainty associated with these cash flows. Hence, companies with higher growth rates, less risk, and greater cash flow generating potential should trade at higher multiples than companies with lower growth, higher risk, and less cash flow potential (Damodaran, 2012a).

In the previous sections we described two approaches of valuing companies, and we argued that the difference between the two valuation approaches is that the assumptions in a relative valuation are implicit and unstated, whereas the assumptions in a fundamental valuation are explicit and stated. In this section, we will provide a bridge between the relative valuation and fundamental valuation in order to reveal and understand the fundamental value drivers of the multiples, which allow us to form initial hypotheses on how fundamental variables influence multiples.

6.1 Multiple Selection

All multiples used in a relative valuation are associated with pros and cons, and the application and relevance of the multiples in given situations are typically related to the shortcomings of the multiples. The shortcomings of each multiple, as a result of the implicit assumptions, are not always revealed until they are seen from a fundamental perspective. Therefore, due to the different assumptions behind each multiple, there has been developed preferences over time when it comes to the application of each multiple best fitted for the different industries, primarily to reduce the time spent on controlling for differences.

Schreiner (2007) defines five groups of multiples used in relative valuation, namely accrual flow
multiples, book value multiples, cash flow multiples, forward-looking multiples, and alternative multiples. The accrual flow multiples are based on earnings-related measures in the income statement, the book value multiples are based on value drivers from the balance sheet, and the cash flow multiples apply cash flow metrics in the denominator. Moreover, the forward-looking multiples use a forecast of the value driver when estimating the multiple, whereas the alternative multiples adjust the multiples for items such as R&D expenses, amortization of intangible assets and so on.

As there are as many multiples as there are accounting numbers, this thesis will focus on four typically applied multiples practitioners may use in their investment decisions. The four multiples in the scope of this thesis are the price to earnings, the price to book value, the enterprise value to EBITDA, and the enterprise value to sales.

6.1.1 The Price to Earnings Multiple

The price to earnings multiple, from now on referred to as the P/E multiple, gained popularity in the early 1930s as a result of the introduction of the value investing style by Benjamin Graham, and is today part of any relative valuations in practice. The P/E multiple is applicable in industries where companies report solid earnings, are subject to uniform accounting policies and operate with similar capital structures (Schreiner, 2007).

Although its popularity among practitioners, the P/E multiple also has some substantial weaknesses. As the earnings origins from the bottom line of the income statement, differences in accounting policies and capital structures affect the earnings. Additionally, the P/E multiple does not provide any meaningful insights if a company has negative or low earnings, which definitely will impact the sample size of the multiple in the analysis (Pereiro, 2002).

6.1.1.1 The P/E Multiple Derived from the Dividend Discount Model

At first, we will derive the intrinsic P/E multiple from the dividend discount model by assuming a stable, growth environment:

\[ P_0 = \frac{Dividend_1}{rE - qEarnings} \]  

(20)

We rewrite the dividend as a function of earnings and the payout ratio:

\[ P_0 = \frac{Earnings_1 \times Pay Out Ratio}{rE - qEarnings} \]  

(21)
We also recognize that the payout ratio is equivalent to 1 minus the retention ratio:

\[ P_0 = \frac{Earnings_1 \ast (1 - Retention \, Ratio)}{rE - gEarnings} \]  
\[ (22) \]

In the following, we rewrite the retention ratio as a function of growth and return on equity:

\[ P_0 = \frac{Earnings_1 \ast (1 - \frac{gEarnings}{ROE})}{rE - gEarnings} \]  
\[ (23) \]

By dividing the forward earnings on both sides, the intrinsic P/E multiple equals:

\[ \frac{P_0}{E_1} = \frac{1 - \frac{gEarnings}{ROE}}{rE - gEarnings} \]  
\[ (24) \]

As well as the trailing intrinsic P/E multiple can be described as:

\[ \frac{P_0}{E_0} = \frac{1 - \frac{gEarnings}{ROE}}{rE - gEarnings} \ast (1 + gEarnings) \]  
\[ (25) \]

Hence, by using the dividend discount model to derive the P/E multiple discloses that the return on equity is a vital value driver of the P/E multiple.

6.1.1.2 The P/E Multiple Derived from the Abnormal Earnings Growth Model

It is also possible to derive the intrinsic P/E multiple from the abnormal earnings growth model, where the model determines the intrinsic value of the company by anchoring on forward or current earnings as well as abnormal earnings growth. If we assume a stable growth phase, the forward intrinsic P/E multiple can be derived as follows:

\[ P_0 = \frac{1}{rE} \ast \left[ E_1 + \frac{g_{Cum. \, div. \, earnings}}{rE - g^{AEG=RI=BVE}} \right] \]  
\[ (26) \]

By dividing the forward earnings on both sides, the forward P/E yields:

\[ \frac{P_0}{E_1} = \frac{1}{rE} \ast \left[ 1 + \frac{g_{Cum. \, div. \, earnings}}{rE - g^{AEG=RI=BVE}} \right] \]  
\[ (27) \]

As can be seen by the derivation, if the company does not create abnormal earnings growth, the forward P/E multiple equals 1/rE, corresponding to the normal forward P/E multiple. Hence, the company should only trade at a premium to its normal P/E multiple if it can generate abnormal earnings growth. Likewise, the trailing intrinsic P/E multiple can be derived as:

\[ P_0 = \frac{(1 + rE)}{rE} \ast \left[ E_0 + \frac{g_{Cum. \, div. \, earnings}}{rE - g^{AEG=RI=BVE}} \right] \]  
\[ (28) \]
By dividing the current trailing earnings on both sides of the equation, the trailing intrinsic P/E multiple equals:

\[
\frac{P_0}{E_0} = \frac{(1 + r^E)}{r^E} \left[ 1 + \frac{g_{0-1} \text{ Cum. div. earnings}}{r^E - g^\text{AEG}=RI=\text{BVE}} \right] \tag{29}
\]

The trailing intrinsic P/E multiple corresponds to the normal trailing P/E multiple, equivalent to \((1 + r^E)/r^E\), in addition to a premium of the abnormal earnings growth. The derivation shows that growth in cum-dividend earnings one period ahead, thus abnormal earnings growth and risk, are determinants for the P/E multiple.

### 6.1.2 The Price to Book Value Multiple

The price to book value multiple, from now on referred to as the P/B multiple, is appropriate for companies in capital-intensive industries where tangible assets are the source of value (Frykman and Tolleryd, 2003). In that regard, both the oil and telecommunication industry are industries that demand significant amounts of capital expenditure and rely on tangible assets that are vital for future earnings and value creation.

The P/B multiple is also very popular among practitioners, as book values are relatively stable over time, which eases comparability as well as it is used as a coarse filter for the so-called value investors in order to detect undervalued stocks. The P/B multiple has also a quite intuitive appeal as book value equals net assets available to common shareholders relative to the market price of the company. Furthermore, companies have seldom negative book values, which will increase the sample size relative to the P/E multiple when conducting the multiple analysis. On the other hand, the application of the P/B multiple requires care as reported numbers for assets are based upon historical costs, which generally are an unreliable indicator of economic value, neither does it reflect a company’s earnings power nor cash flows (Schreiner, 2007).

#### 6.1.2.1 The P/B Multiple Derived from the Residual Income Model

The intrinsic P/B multiple can be derived from the residual income model, which anchors on the book value of equity and residual incomes of the company. By assuming a stable, growth environment, the intrinsic P/B multiple can be expressed as:

\[
P_0 = B_0 + \frac{RI_1}{r^E - g^RI} \tag{30}
\]
The residual incomes can be expressed as the difference between the return on equity and cost of equity multiplied by the book value of equity, which results in the following expression:

$$P_0 = B_0 + \frac{(ROE_1 - r^E) \cdot B_0}{r^E - g^{RI}}$$  \hspace{1cm} (31)

The growth rate of the residual incomes, assuming a constant return on equity, is equal to:

$$g^{RI} = \frac{(ROE_1 - r^E) \cdot B_0}{(ROE_0 - r^E) \cdot B_{-1}} = \frac{B_0}{B_{-1}}$$  \hspace{1cm} (32)

Hence, we can substitute the growth in residual incomes with the growth in book value of equity, since the growth comes from the growth in book value of equity and not an increase in return on equity. By dividing the book value of equity on both sides, the intrinsic P/B multiple equals:

$$\frac{P_0}{B_0} = 1 + \frac{(ROE_1 - r^E)}{r^E - g^{BVE}}$$  \hspace{1cm} (33)

The derivation shows that the intrinsic P/B multiple is determined as the normal P/B multiple, which equals 1, in addition to the difference between the return on equity and cost of equity growing at a constant rate $g$ discounted to present. Hence, if the company does not generate any residual incomes, the company should trade at the reasonable P/B multiple of 1. In order to justify a valuation above its book value of equity, the company has to generate residual incomes above the cost of equity going forward. The derivation of the intrinsic P/B multiple reveals that the return on equity, growth in book value of equity, and cost of equity are key value drivers for the multiple.

6.1.3 The Enterprise Value to EBITDA Multiple

The enterprise value to EBITDA multiple, from now on referred to as the EV/EBITDA multiple, is a darling among practitioners and there are several reasons for speaking in favor of the multiple. First, enterprise value multiples are less affected by capital structure decisions than equity-based multiples, since it measures the non-levered value of the company. Second, EBITDA is a measure of operating performance and are not affected by different tax or depreciation and amortization regimes, as well as it is a proxy for cash flows. Yet, the multiple is still affected by differences in capital intensity, measured as depreciation expenditures as a percentage of EBITDA, and thus suitable for the investigated industries although using EBIT is advantageous (Schreiner, 2007). Lastly, as EBITDA is close to the top of the income statement, most companies have positive values. This implies that the sample size of the multiple analysis will not be necessarily affected by negative values, and thus strengthening the robustness of the multiple.
6.1.3.1 The EV/EBITDA Multiple Derived from the Discounted Cash Flow Model

The discounted cash flow model estimates the enterprise value by forecasting future free cash flows and concentrates on the investing and operating activities of the firm. By assuming a stable growth and constant factors across time, the intrinsic EV/EBITDA multiple can be derived in the following manner:

\[
EV_0 = \frac{FCFF_1}{WACC - g^{FCFF}} = \frac{EBIT_1 \times (1 - t_c) + Depreciation - \Delta NWC - CAPEX}{WACC - g^{FCFF}} = \frac{EBIT_1 \times (1 - t_c) - (CAPEX - Depreciation + \Delta NWC)}{WACC - g^{FCFF}}
\]

\[
EV_0 = \frac{EBIT_1 \times (1 - t_c) - Reinvestments_1}{WACC - g^{FCFF}}
\]

By expressing the reinvestments as a percentage of EBIT \((1 - T_c)\), we can express the equation as:

\[
EV_0 = \frac{EBIT_1 \times (1 - t_c) \times (1 - Reinvestment Rate_1)}{WACC - g^{FCFF}}
\]

We can also rewrite the growth rate in FCFF as:

\[
g^{FCFF} = \frac{EBIT_1 \times (1 - t_c) \times (1 - Reinvestment Rate_1)}{EBIT_0 \times (1 - t_c) \times (1 - Reinvestment Rate_0)}
\]

If we assume that the reinvestment rate is constant, the growth in FCFF equals the growth rate in the operating income. By dividing the EBIT on both sides, the forward EV/EBIT multiple can be denoted as:

\[
\frac{EV_0}{EBIT_1} = \frac{(1 - t_c) \times (1 - Reinvestment Rate_1)}{WACC - g^{Operating Income}}
\]

Since we assume constant growth on EBIT \((1 - T_C)\) and a constant reinvestment rate, we can express the reinvestment rate as a function of ROIC and growth:

\[
\frac{EV_0}{EBIT_1} = \frac{(1 - t_c) \times \left(1 - \frac{g^{Operating Income}}{ROIC}\right)}{WACC - g^{Operating Income}}
\]

Lastly, if we express EBIT as EBITDA \((1 - D)\), where \(D\) is depreciation expenditures as a percentage of EBITDA, and further divide both denominators with \((1 - D)\) and \((1 + g)\), we obtain the current intrinsic EV/EBITDA multiple:

\[
\frac{EV_0}{EBITDA_0} = \frac{(1 - t_c) \times \left[1 - \frac{g^{Operating Income}}{ROIC}\right] \times (1 - D)}{WACC - g^{Operating Income}} \times (1 + g^{Operating Income})
\]
The derivation underpins that profitability, measured by ROIC, and growth are positive determinants of the EV/EBITDA multiple, whereas the capital intensity, measured as depreciation expenditures as a percentage of EBITDA, risk and tax are negative factors for the EV/EBITDA multiple.

6.1.4 The Enterprise Value to Sales Multiple

The enterprise value to sales multiple, hereinafter referred to as the EV/Sales multiple, is based on the very top of the income statement and suitable for comparisons of cyclical and immature companies, primarily when operating performance measures fail to represent the long-term potential or are negative during the downturn of the cycle (Koller et al., 2010; Schreiner, 2007).

However, as the enterprise value is scaled to an item at the top of the income statement, it ignores all information about operating performance and efficiency (Benninga and Sarig, 1997). The multiple also implicitly assumes that the operating margins are similar among companies in the peer group, which is rarely the case. As a final remark, the EV/Sales multiple gained increased attention during the rise of technology and internet stocks in the mid and late 1990s, but lost its attractiveness since the dot-com bubble burst in 2001 (Schreiner, 2007).

6.1.4.1 The EV/Sales Multiple Derived from the Discounted Cash Flow Model

As the EV/EBITDA multiple, the EV/Sales multiple can also be derived from the discounted cash flow model. By dividing sales on both sides, as well as both denominators with \(1 + g\), we can express the intrinsic EV/Sales multiple:

\[
\frac{EV_0}{Sales_0} = \frac{EBIT_{Sales_1} * (1 - Reinvestment Rate_1) * (1 - t_c)}{WACC - g^{Operating Income}} * (1 + g^{Operating Income})
\]  

(41)

By recognizing that \(EBIT_{Sales_1}/Sales_1\) is the EBIT-margin, it yields:

\[
\frac{EV_0}{Sales_0} = \frac{EBIT\ Margin * (1 - Reinvestment Rate_1) * (1 - t_c)}{WACC - g^{Operating Income}} * (1 + g^{Operating Income})
\]  

(42)

The numerator in the above multiple expression is equivalent to the FCFF as a percentage of sales, referred to as the FCFF-margin, and can be written as:

\[
\frac{EV_0}{Sales_0} = \frac{FCFF\ Margin}{WACC - g^{Operating Income}} * (1 + g^{Operating Income})
\]  

(43)

Thus, the derivation shows that the intrinsic EV/Sales multiple is affected by the EBIT-margin, FCFF-margin, tax, growth, and risk.
### 6.1.5 Summary of Theoretical Multiple Drivers and Hypothesis

In order to get a holistic view of the intrinsic multiples, we have summarized the derivation and emphasized the key value drivers of each multiple in the figures below.

#### Table 1: Summary of Intrinsic Multiples and Key Value Drivers

<table>
<thead>
<tr>
<th>Multiple</th>
<th>Valuation Model</th>
<th>P/B Model</th>
<th>P/E Model</th>
<th>P/E Growth Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Model</td>
<td>Residual Income Model</td>
<td>[ \frac{P_0 - B_0 + \frac{R_1}{r_E - g_{B1}}} {B_0} ]</td>
<td>[ \frac{P_0 - \frac{\text{Dividend}} {r_E - g_{Earnings}}} {B_0} ]</td>
<td>[ \frac{(1 + r_E) \times \left[ \frac{\text{Cum. disc. earnings}} {r_E - g_{Earnings}} - (1 + g_{Earnings}) \right]} {B_0} ]</td>
</tr>
<tr>
<td>Intrinsic Multiple</td>
<td>EV/EBITDA Model</td>
<td>[ \frac{P_0}{B_0} = \frac{1 + \left( \frac{\text{ROE}<em>1 - r_E}{r_E - g</em>{B1}} \right)} {B_0} ]</td>
<td>[ \frac{P_0}{B_0} = \frac{1 - \frac{\text{Earnings}} {r_E - g_{EBITDA}}} {B_0} \times \left(1 + g_{Earnings}\right) ]</td>
<td>[ \frac{P_0}{B_0} = \frac{(1 + r_E) \times \left[ \frac{\text{Cum. disc. earnings}} {r_E - g_{EBITDA}} - (1 + g_{Earnings}) \right]} {B_0} ]</td>
</tr>
<tr>
<td>Key Value Drivers</td>
<td>ROE, Growth in Book Value, Cost of Equity</td>
<td>ROE, Growth in Earnings, Cost of Equity</td>
<td>Cost of Equity, Cum-Dividend Growth Rate, Growth in Earnings</td>
<td></td>
</tr>
</tbody>
</table>

Figure 9: Summary of the Intrinsic P/B and P/E Multiple and Key Value Drivers

<table>
<thead>
<tr>
<th>Multiple</th>
<th>EV/EBITDA Model</th>
<th>EV/Sales Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Model</td>
<td>Discounted Free Cash Flow Model</td>
<td>[ \frac{EV_0}{EBITDA} = \frac{FCFF_1}{WACC - g_{CFPP}} ]</td>
</tr>
<tr>
<td>Intrinsic Multiple</td>
<td>Discounted Free Cash Flow Model</td>
<td>[ \frac{EV_0}{EBITDA} = \frac{FCFF_1}{WACC - g_{CFPP}} ]</td>
</tr>
<tr>
<td>Key Value Drivers</td>
<td>Capital Intensity, ROIC, Reinvest. Rate, Growth in Operating Income, Cost of Capital, Tax</td>
<td>[ \frac{EV_0}{EBITDA - \text{Reinvest. Rate}} \times \left( \frac{1 - \text{Reinvest. Rate}} {WACC - g_{Operating Income}} \right) \times \left(1 + g_{Operating Income}\right) ]</td>
</tr>
</tbody>
</table>

Figure 10: Summary of the Intrinsic EV/EBITDA and EV/Sales Multiple and Key Value Drivers

The derivation of the intrinsic multiples has revealed that practitioners cannot conduct a relative valuation without thinking about the critical value drivers of the multiple. Typically, practitioners solve the issue of company dissimilarity by using industry classification as a proxy for company comparability, which relies on the assumption that the companies in the industry share the same economic characteristics in terms of profitability, growth, and risk. However, companies operating in the same industry do not necessarily possess the same level of profitability, growth, or risk and thus should not trade at the same multiple. Therefore, in order to conduct a robust relative valuation from a theoretical point of view, it is vital to control for differences in the critical value drivers across companies in the peer group. Based on the theoretical framework of this thesis, we have defined the following hypothesis, which anchors on the theoretical relations between the relative and fundamental valuation approach.
Hypothesis 1.1

“There is a ... relationship between the ... variable and the ... multiple.”

Figure 11: Summary of the Expected Relationships between the Multiples and Independent Variables

<table>
<thead>
<tr>
<th>Theoretical</th>
<th>RM/ROIC</th>
<th>Margin</th>
<th>Growth</th>
<th>Capital Intensity</th>
<th>Reinvestment Rate</th>
<th>Beta</th>
<th>Profit Margin</th>
<th>Operating Liability</th>
<th>Financial Leverage</th>
<th>Growth Risk</th>
<th>Quality</th>
<th>Oil Price (EFP NYM)</th>
<th>10-Year Treasury</th>
</tr>
</thead>
<tbody>
<tr>
<td>P/B</td>
<td>Positive</td>
<td>Positive</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Positive</td>
<td>Positive</td>
<td>Positive</td>
</tr>
<tr>
<td>P/E</td>
<td>Positive</td>
<td>Positive</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Positive</td>
<td>Positive</td>
<td>Positive</td>
</tr>
<tr>
<td>EV/EBITDA</td>
<td>Positive</td>
<td>Positive</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Positive</td>
<td>Positive</td>
<td>Positive</td>
</tr>
<tr>
<td>EV/Sales</td>
<td>Positive</td>
<td>Positive</td>
<td>Positive</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Negative</td>
<td>Positive</td>
<td>Positive</td>
<td>Positive</td>
</tr>
</tbody>
</table>

7 Data

Answering this thesis’ research question satisfactorily requires a vast amount of data and data management; hence, it is essential to ensure that the data we extract and prepare as input is reliable. The purpose of this section is to disclose how we choose to screen companies and the approach to constructing a database that will be subject of the linear regression analysis, leaving us with several data sets comprised of relevant and reliable data. Constructing such a database requires an organized refinement process with no room for mistakes, as obtaining correct results from the analysis solely relies on the input being flawless.

7.1 Screening and Data Extraction

The scope of this thesis extends to companies that have sufficient price and accounting data publicly available. As the dependent variables, the multiples, all are comprised of the market value of equity we would need a certain level of liquidity in the assets to make sure the pricing is as accurate as possible, which naturally limits us to companies that have been or are publicly listed. This includes companies that have been delisted or at any point in time has been listed with sufficient publicly available data. As we conduct quarterly, cross-sectional linear regressions, firms could potentially appear and disappear at different points in time, effectively preventing survivorship bias.

For the screening process, we used Bloomberg’s Equity Screening function where Bloomberg offers a set of different criteria one can set to refine one’s search in their database. In addition to searching the security universe for both active and delisted companies, security attributes were chosen to display primary shares only. Furthermore, the screening was restricted to companies with an
International Securities Identification Number (ISIN) containing data. We decided to leave the Bloomberg Industry Classification System (BICS) as default when defining the industries during the screening process. In the telecom sector companies that are categorized as carriers and resellers were both included to attain a broad diversity of companies in this sector. As the concept is to compare an industry that is not reliant on external price setting, obtaining a sizeable, diversified sample of firms is desirable to mitigate idiosyncratic risk. Selecting companies in the oil industry however, is slightly more complex as the company’s exposure to the oil price depends on their core business and their position in the value chain. All companies within the oil industry are more or less exposed to the oil price, but subsectors such as oil service companies will have their revenue be more reliant on the oil producers’ (upstream segment) investments, rather than the oil price directly. To include companies that have a substantial share of their revenue stemming from other sources such as transportation, storage or refining (mid- and downstream segment) will lead to more noise in the results and will, therefore, be excluded. This means that the sample will be limited to companies that operate in the upstream part of the value chain, hence, restraining us to the exploration and production segment. This equity screening process leaves a sample of 1,149 telecom companies and 1,804 E&P companies.

To extract the Bloomberg data Excel’s “Bloomberg Historical Data” (=BDH()) function were used, which can be accessed through installing the Bloomberg Add-in. The firm betas and price data, such as market value and share prices, were extracted. For beta values, the raw beta were chosen. These raw historical betas measure the volatility of the stock relative to the volatility to its respective market index. This provides us with betas updated each quarter that are all calculated based on weekly share prices over the last three years. A three year period was chosen because an extended period might force the beta to neglect to reflect recent changes in a company’s risk profile, while a shorter period could contain too little and unstable data. The recommended time frame is from two to five years, depending on the frequency of observations (Damodaran, 2012a). The market values represent the total market value of all of a company’s outstanding shares stated in the pricing currency, and the share price is the last registered market capitalization divided by the number of outstanding shares at each quarter. Hence, the share price is not adjusted for dividends as the market capitalization is subtracted if dividends are paid to shareholders. This should not be a huge problem, although it might have a downward impact on some of the calculated trailing multiples for companies that pay out dividends. The screening process is depicted in Appendix 14.1.
Next, the accounting data was fetched from Wharton’s COMPUSTAT database. The tickers and ISIN-numbers from the equity screening were fed into the database along with nineteen accounting variables carefully selected in order for us to calculate the value drivers derived from the multiples in section six. COMPUSTAT contains company data back to 1969 for U.S. companies, and 1988 for companies outside the U.S. With quarterly data for all companies approximately 38,000 observations for each variable in the E&P industry were obtained, and 28,000 for each variable in telecom industry. COMPUSTAT did not have data from all the companies in its database, which left the sample with a total of 715 companies within E&P and 609 within telecom that makes up the subject for the analysis. The full list of companies included in this thesis can be found in Appendix 14.1. We trust that Wharton ensures that the COMPUSTAT database contains correct accounting data; however, we conducted several samples of financial statements to ensure quality, and they all came out successful.

Lastly, non-company specific data such as the oil price and interest rate was provided by investing.com and U.S. Department of Treasury, respectively. To represent the oil price, crude oil WTI futures were chosen due to the larger share of U.S. companies in the sample. Choosing between the WTI and the Brent oil price should not make a difference as they are highly correlated with a relatively stable spread. The interest rate, however, was chosen to be represented by the U.S. Government’s ten-year treasury, also due to the high presence of American companies. Interest rates are not consistent across the different nations and could vary greatly. The results regarding the interest rate should, therefore, be interpreted with care, although we believe that the timeline is sufficiently long enough to capture the broader trends in the world economy.

Since both variables consist of quarterly data, these variables will be constant in the quarterly linear regressions. Hence, the variables will only be represented in the refined linear regression models as they would be omitted from the quarterly linear regressions. Moreover, we also wish to examine to what extent the inclusion of the external variables will improve the refined linear regression models compared to the pooled linear regression models.

### 7.2 Data Preparation

As all the data needed for the analysis is extracted, we now possess several large sets of data that have to be put together to make up a useful database. This requires us to match all the data to fit the companies and timeline. The current data will also require further cleaning to get pure
data sets that we can feed into the linear regression model. This is a cumbersome process that is essential to get right as it makes up the fundament of the thesis.

The data that was fetched from Bloomberg is aligned horizontally in Excel; each company with one column containing a timeline, beta, market value of equity, share price and a target price (see Appendix 14.1). To organize this data we constructed a macro that created a new data set for each of the variables; one column with a timeline, and all company data matched to the timeline in the following columns. The data sets were then merged into the data sets containing the accounting figures from COMPUSTAT combining Excel’s =INDEX() and =MATCH() functions, matching the data by date and tickers/ISIN-numbers. The result is a raw database with all variables aligned horizontally in columns, and the companies, each with its timeline, stacked vertically (see Appendix 14.1). Before cleaning the data, all multiples and accounting variables that represent the value drivers will be calculated. Instead of extracting multiples and value drivers directly, we have chosen to download the raw data needed to calculate them ourselves. This is to ensure that comparisons can be made validly and that there is consistency in how metrics are calculated.

7.2.1 Dependent Variables

Representing the valuation metrics in this thesis, we decided to go for multiples as opposed to absolute market value. The research of Abrams (2012) find arguments that the scaled valuation metrics as dependent variables tend to reduce the likelihood of heteroscedasticity, but may result in a lower explanatory power for the linear regression model. Furthermore, using multiples implies easier comparison across company size and companies in nations using different currencies.

In order to calculate the multiples, we make use of the accounting data from WRDS. The P/E and P/B multiples both have market cap as the numerator, i.e., the last registered market capitalization each quarter. Calculating the numerators for the enterprise multiples, however, requires us to know the company’s net interest-bearing debt (NIBD). The NIBD should be the market value of the net debt in which the company has to pay interest on. The market value of NIBD is not as readily available as the market value of equity due to liquidity in the asset and inconsistent complex debt structures and has therefore been calculated as long term debt and debt in current liabilities, less cash, and short-term investments.
When calculating the multiples’ denominators we used 12-month trailing accounting numbers for all except the P/B multiple. The P/B multiple uses the current market capitalization, divided by the book value of equity previous quarter. The P/E, EV/EBITDA and EV/Sales multiples use the 12-month trailing net earnings (NE), earnings before interest tax, depreciation and amortization (EBITDA), and revenue, respectively. This implies that the numerator is divided by the last four quarters accumulated, and is therefore omitted if there are not four consecutive quarters containing data. As investors do not have access to current quarter’s accounting figures before the report is released the consecutive quarter, all numbers reported from financial statements (IS and BS) have been lagged one quarter relative to the market values.

\[ \frac{P}{E} = \frac{MVE_t}{NE_{t-1} + NE_{t-2} + NE_{t-3} + NE_{t-4}} \] (44)

\[ \frac{P}{B} = \frac{MVE_t}{BVE_{t-1}} \] (45)

\[ \frac{EV}{EBITDA} = \frac{MVE_t + NIBD_{t-1}}{EBITDA_{t-1} + EBITDA_{t-2} + EBITDA_{t-3} + EBITDA_{t-4}} \] (46)

\[ \frac{EV}{Sales} = \frac{MVE_t + NIBD_{t-1}}{Revenue_{t-1} + Revenue_{t-2} + Revenue_{t-3} + Revenue_{t-4}} \] (47)

The last adjustments made to the dependent variables were to remove all negative multiples. A negative valuation multiple implies that one, in theory, pays less than zero for a company, which does not make economic sense. Removing negative multiples is likely to cause a positive skewness in the data; however, it also enables us to log-transform the dependent variables if it should be necessary for the analysis. Log-transforming the variables could be required if we discover non-linear relationships between the dependent and independent variables, or to remove a positive skewness in the data and obtain more symmetrically distributed residuals.

### 7.2.2 Independent Variables

Section six described the theoretical relationship between the multiples and the fundamental value drivers and laid the foundation for what metrics we wish to include in the analysis. We define four primary value drivers, namely: profitability, cash flow, growth, and risk. Each of the value drivers comprises of a set of carefully selected metrics that will represent the independent variables. As mentioned earlier we extracted raw accounting numbers and calculated metrics ourselves to ensure
consistency. There is, however, likely that not all 1,324 companies in the sample use the same accounting practices. For example, industries like oil exploration and production and telecommunication companies often make substantial investments in infrastructure; hence, extensive development and exploration costs occur. The probability that the individual companies capitalize such costs differently, both within and across nations, are reasonably high. Adjusting for such accounting differences in a sample the size that is analyzed here is beyond the scope of this thesis, as we do not obtain information regarding the individual differences.

The fact that the metrics used in the analysis is derived from the multiples reduces the probability that the findings in this thesis are a result of data mining or similar bias. Note also that all the metrics representing value drivers are chosen to be ratios, rates, and margins. Like the multiples, using such relative metrics allow us to compare companies despite differences in size and currency freely.

In calculating the metrics, we made revenue and all stages of earnings into 12-month trailing earnings. Hence, all margins (EBITDA, NOPAT, and EBIT) are trailing earnings as a percentage of trailing revenue. The cash flow metrics (OFC-, FCFF-margins, reinvestment rate, and capital intensity) also contain accounting figures from the balance sheet such as NWC, OPEX, and CAPEX. To calculate the cash flow metrics we trailed the changes in these balance sheet numbers in the matching 12-month period of trailed earnings to ensure periodical matching of IS and BS numbers. Moreover, return on equity and return on invested capital were calculated by dividing trailing NE and NOPAT by the previous quarter’s book value of equity \( (BVE_{t-1}) \) and invested capital \( (IC_{t-1}) \), respectively. The invested capital was found as the sum of net interest-bearing debt and book value of equity. Lastly, the risk metrics use accounting numbers from the same quarters. Hence, profit margin risk is calculated by dividing trailing OPEX with trailing revenue in the matching quarters, operating liability risk by dividing current liabilities with invested capital and financial leverage through dividing the NIBD over MVE. Finally, the remaining independent variables are external figures that are not directly derived from the companies’ financial statements.

7.2.3 Preparing for Linear Regressions

After finishing calculating all variables, the data set went through a final round of cleaning where all observations that did not have values in the variables we analyze, were removed. These are mainly variables that lack observations due to trailing variables that require data in four consecutive quar-
ters, as well as first-quarter observations that require one-time lag to exhibit a return, such as ROE.

Having cleaned the data, we now have two databases; one for the oil exploration and production industry, and one for the telecom industry. These databases are further split into four, one base for each of the valuation multiples, with the different databases containing the variables that we sought relevant for the respective variables, based on all prior assumptions. This setup leaves us with eight databases; one for each multiple in each industry. Moreover, one such database will be comprised of a data set containing all quarters for the pooled linear regressions, as well as one data set for each of the quarters over the entire period. This structure allows us to more easily write code in STATA to run linear regressions on the data.

We have chosen to use STATA to run linear regressions because of the vast amount of data needed to be processed. STATA’s more simple layout allows the linear regressions to run more smoothly and its user configurations enable us to more easily test and adjust for assumptions we have made in regard to the linear regression models. We designed the code in STATA to generate and document all required output in an automated process. In this way, we managed to run over 1,000 regressions without needing to document all output from each regression manually.

8 Industry and Descriptive Analysis

The purpose of this section is to provide an overview of the two industries and how the value drivers and multiples have behaved historically. We want to study the evolvement of different characteristics to see which areas might be interesting to observe more in detail in the analysis. To do this, we map out the metric’s value over time to study the relationship between them and how they reacted both to and following extraordinary events in history. In practice, this means that we calculate the median value of the metrics and multiples in each quarterly sample and see how the values have behaved throughout time. Along with the interest rate and oil price, displaying these graphically will provide an overview and serve as an indicator for interesting relationships.

8.1 The Oil Industry

The oil industry includes the global processes of exploration, extraction, refining, transporting, and marketing of petroleum products. The industry is usually divided into three major components; upstream, midstream, and downstream. The upstream sector includes searching for potential
underground or underwater crude oil and natural gas fields, drilling exploratory wells, and subse-
quently drilling and operating the wells that recover and bring the crude oil or raw natural gas
to the surface. The midstream sector involves transportation (by pipeline, rail, barge, oil tanker
or truck), storage, and wholesale marketing of crude or refined petroleum products. Pipelines
and other transport systems can be used to move crude oil from production sites to refineries and
deliver the various refined products to downstream distributors. The downstream sector is the
refining of petroleum crude oil and the processing and purifying of raw natural gas, as well as the
marketing and distribution of products derived from crude oil and natural gas. The downstream
sector ultimately reaches consumers through products such as gasoline or petrol, kerosene, jet fuel,
diesel oil, heating oil, fuel oils, lubricants, waxes, asphalt, natural gas, and liquefied petroleum
gas (LPG) as well as hundreds of petrochemicals (CAWPC, 2019; PSAC, 2019). As we briefly
explained in section seven, the scope of this paper will extend to the upstream segment that mainly
has operations within the exploration and production of oil. We believe this will provide us with
the more clear-cut results as these have more direct exposure to the oil than the other parts of the
value chain.

8.1.1 External Factors

The oil price, like the price of most products, is dependent on supply and demand. What sepa-
rates the oil market from other markets is that the large producers, mostly made up of national
oil companies, have been able to maintain a cartel. This is because these producers are countries,
and are therefore not subject to the same policies that prevent companies from engaging in such
cooperative operations to control price. In addition to this, crude oil reserves are stored by several
countries globally, which makes the current reserves yet another factor that affects the price of oil.
Due to inadequate and slow reporting of numbers, adjusting production is difficult, thus generating
at times significant fluctuation in the oil price. Individual oil companies are therefore price takers
in a market that are cyclical by nature and characterized by volatility.

Figure 12a shows how the median market values have evolved over time along with the oil price.
The graph indicates a high correlation between the oil price and the market capitalization of the
E&P companies. Note that the number of observations is lower in the earlier years, as well as at
the last quarter in the sample. Fewer observations could be an explanation to why the market
capitalization is slightly more extreme in the late 1980s’, and the last quarter of 2018, however,
significant events did occur that is likely to have affected the market values and oil price.
At first glance, the oil price is seemingly stable up until the 2000s’, after which it finds a higher level and becomes somewhat more volatile. However, studying the numbers more in detail will show that the oil price went from $17 up to $39.6 and down again to $19.6 in the peak that is observed around the 1990s’, i.e., more than doubling followed by something close to a 50% price reduction. The trigger of this rally is the Gulf War during 1990s when Iraq invaded Kuwait and caused a massive reduction on the supply side (Hamilton, 2011). The volatility becomes more apparent on the logarithmically scaled graph depicted in figure 12b, where we can observe the fluctuations throughout the entire period. In the aftermaths of the Gulf War, from 1991 to 1997, global demand increased steadily, and global oil production rose with as much as six barrels per day. A marginal demand surplus caused the price to rise slowly up until the Asian financial crisis in 1997, after which the demand fell and caused an imbalance in the markets (Speight and Fantacci, 2011).

The world experienced considerable economic growth in the next couple of decades where the former agricultural countries increased oil consumption significantly and generated a large demand surplus. This caused the oil price to rise steadily until the peak north of $140 before the financial crisis hit, and the consumption plummeted (Hamilton, 2011). After taking a big hit, hitting the $40s’, financial stimulation such as quantitative easing and lower interest rates incentivized consumption, and the oil price started to rebound. The growth in the BRICS countries started to slow after 2010, and U.S. production of shale oil was becoming competitive at these high prices. The North-American region soon reached a level where they became close to self-sufficient and did not have the same need to import oil. OPEC, in fear of losing their market share, chose not to adjust production to maintain high prices, in order to knock out competitors in shale oil that currently
had higher break-even points. The supply surplus forced prices to a 12-year low, down to $26 USD/Bbl. Since then we have experienced a volatile increase, peaking around $75 with a current state around $50-$60.

Figure 13a displays how the EV/EBITDA multiple has evolved relative to the oil price. It appears that the multiple has been quite volatile, mostly valuing the companies between four and eight times their EBITDA. From the graph, it appears that the multiple took the most significant hits in 1986, 1999, 2007 and 2016, consistent with the historical events described above. Note that some peak at the beginning of a crisis and some peaks are in the aftermaths. In 2007, the multiple fell due to the deep financial crisis that mainly hit the valuation of the companies in the first round, before actually affecting the earnings. Another story would be the case in the period of 2014-2016 where the oil price fell while the rest of the stock market remained stable. The multiple is likely to have been driven by decreasing earnings while valuations did not experience a correction until late 2016.

![Figure 13](a) EV/EBITDA and Oil Price  (b) P/E and 10-Year U.S. Treasury Rate

A large amount of volatility can also be observed in the P/E multiple. In figure 13b, we can see a falling trend in the P/E multiple over the first half of the period while shifting toward a more mean-reverting multiple valuation of fifteen times trailing earnings in the second half. This implies that the oil companies, in general, reached higher valuation on their net earnings last century than they have in this century. The figure also depicts the movement in the P/E multiple relative to the U.S. 10-year Treasury rate. The figure displays a declining rate almost throughout the entire period, before ending the trend in 2016 when the U.S. decided to stop the quantitative easing and began to increase the interest rate. At this point, the world had experienced a long period of economic growth, and the macroeconomic outlook started to look promising. The figure shows that
the interest rate and P/E multiple have experienced similar trends; however, it is hard to conclude on a particular reason why they seem to correlate. Declining interest rates do cause increasing valuations in most contemporary models used by analysts, as low rates imply cheaper financing and increased consumption, leading to increased earnings and valuations for the companies as well as lower discounting rates. Looking back at the market valuations in figure 12 one can see how the valuations have found high levels in later time, and it is likely that the high oil prices and economic stimuli through quantitative easing and low interest rate have been significant factors in this evolvement.

![Figure 14: (a) EV/Sales and Oil Price (b) P/B and Oil Price](image)

Looking at figure 14a we can see the median EV/Sales multiple graphed against the oil price. Not surprisingly, the EV/Sales multiple has evolved quite similar to the EV/EBITDA multiple. It has the same reaction to the same events as seen in figure 13a, maintaining a high level during a large part of the 90s’ and up to the financial crisis, and experiencing an increase between 2014 and 2016. Lastly, figure 14b depicts the oil price graphed against the P/B multiple. Just like the P/E ratio, the P/B multiple appears to find a lower level in the period after the financial crisis. As seen from the illustrations, the enterprise multiple maintains a higher level than the equity multiple after 2010, which could be due to the high leverage in the industry. However, not surprisingly it seems that these graphs indicate that external factors definitely have affected the valuation of the firms operating in the field of oil exploration and production.

### 8.1.2 Multiple Breakdown

To further analyze the fluctuations of the multiples, it is necessary to assess whether the changes in the multiples at different points in time are caused by the investor’s valuation of the companies, or if it is fundamental changes causing it. Graphing the numerator and the denominator along with
the multiple is helpful in this process. Due to the lack of non-US COMPUSTAT data before 1988, there are few observations before this, which is why most of the analysis starts at this point.

Starting with the P/B multiple, the sample shows a median of 1.76 for the entire period, which indicates that the market on average has priced the companies at a 76% premium to their book values. Looking at Figure 15a, it appears that the book and market values of E&P companies spiraled down from 1988 before it broke out of the trend in the early 90s’ presumably due to a stabilization of the oil markets in the aftermaths of the Gulf War. The following years were characterized by market values increasing more rapidly than book values, consequently forcing the P/B multiple up. The effect was reversed in 1997 when the oil price took a hit from the Asian markets. The same case occurred around the financial crisis caused by the U.S. housing market, resulting in an E&P sector that on average was priced at a discount late in 2008 and into 2009. The next time the sector would see a discount was in 2015 when the market valuations in the sector saw a significant correction as a function of an oil price in free fall, while the book values remained relatively stable due to the incredible cost reduction in the firms, effectively avoiding large deficits.

Figure 15: (a) P/B, and Log-Transformed Market Capitalization and Book Value of Equity  (b) P/E, and Log-Transformed Market Capitalization and Earnings

Figure 15b displays the market values of the P/E sample against their net earnings. The median P/E for the entire sample is 14.54 and appears more volatile due to the large fluctuations in the earnings. The earnings are more sensitive to the oil price and react faster to changes in the macroeconomic environment than the book value of equity, and investors are likely to base the valuation on the earnings, which is why the two are more synchronized. Looking closer into the co-movement one will notice how the market will react to the events around 1997, 2007 and 2014 faster than it shows in the earnings, causing downward spikes. That the earnings lag behind the
market values indicates that investors react to changes in the oil price, predicting lower earnings for the companies in the future. The oil price is graphed along with the earnings and market values in Appendix 14.2.1. Furthermore, the industry median EV/EBITDA and EV/Sales are 6.61 and 3.22 respectively over the period.

8.1.2.1 Profitability and Cash Flow

In section six we covered the theory regarding the value drivers for each of the multiples. We found that positive return on equity and earnings growth should be closely related to driving profitability and hence equity multiples upward. We also found the return on invested capital, growth and good margins to positively drive the profit and enterprise multiples, while capital intensity and reinvestment rate, amongst other things, should be negatively related to profitability.

Starting with the equity multiples, figure 16a illustrates the relationship between the P/B multiple and return on equity. The graph seems to indicate a positive correlation between the two variables in line with theory and the hypothesis. However, regarding ROE and ROIC and their respective multiples, the P/B multiple is the only multiple that displays the positive relationship that we expected. The rest of the illustrations concerning the multiples and ROIC and ROE can be found in Appendix 14.2.1. Similarly, from deriving the dividend discount model, we expect to see a negative relationship between the P/E and profit margin risk as illustrated in figure 16b. The relationship does not appear to be as clear as the P/B and ROE variables as they display a synchronized negative trend up until the shift between 2002 and 2003 after which it appears that they start to move opposite of each other before becoming synchronized gain at the end of the period.

Figure 16: (a) P/B and ROE  (b) P/E and Profit Margin Risk
Figure 17: (a) EV/Sales and Reinvestment Rate (b) EV/EBITDA and Capital Intensity

Figure 17a illustrates how the EV/Sales multiple is affected by the median reinvestment rate. From deriving the multiple, we found that the reinvestment rate, in theory, should have a negative impact on the EV/Sales multiple as it impacts the firm’s cash flow. This seems to hold for most of the time; however, there is a lack of consistency throughout the period. Another relationship that should, according to theory, be negatively related is the capital intensity’s effect on the EV/EBITDA multiple. Figure 17b displays a graph of the variables, and as we see, the two do not indicate that there is a negative correlation.

8.1.2.2 Growth

From section six we found that growth in earnings should have a positive impact on all multiples. Figure 18a illustrates the positive relationship between equity growth and P/B multiple as expected. Note how both the growth in book value of equity and the return on equity in figure 16a peaks around the 2000s’. Looking back at the oil price we can see that the oil price did a 257 percent return from 1998 up to 2000 which can explain the great earnings growth in the industry. At the same time, we can see that the multiples upward momentum are cut off in the mid-2000s’, which presumably was a consequence of the broader bear market for stocks caused by the so-called dot-com bubble burst. A somewhat more ambiguous relationship can be seen in figure 18b. The graph indicates a positive relationship, however, the growth in EBIT depicts lots of volatility.
8.1.2.3 Risk

With high risk comes great reward, and as previously discussed, beta is a measure that represents the riskiness of the stock in financial theory. Hence, higher risk means that investors require a high premium to hold it, leading to a lower valuation and a lower multiple. Figure 19a illustrates the inverted relationship between the EV/EBITDA multiple and beta, and seems to hold almost through the entire period except from a short period between 2001 and 2004. Looking at figure 19b we can observe that the relation is changing from positive to negative over short time intervals, while displaying a similar overall trend for the entire period. The rest of the illustrations between the multiples and their assumed value drivers within profitability, growth and risk can be found in Appendix 14.2.1 concerning the descriptive analysis.
8.1.3 Summary and Hypothesis Refinement

After a closer analysis of the graphical relationship between the quarterly median multiple values and the identified value drivers in the E&P industry over time, the observations suggest a revision of the initial hypothesis. The underlining of the relationship indicates a revision from hypothesis 1.1.

Hypothesis 1.2

“There is a ... relationship between the ... variable and the ... multiple in the E&P industry.”

![Figure 20: Refined Hypothesis for the E&P Industry](image)

8.2 The Telecommunication Industry

In the early 1990s’, during the rise of the Internet, operating companies in the telecommunication industry were valued at a fraction of what we see today. Commercial Internet Service Providers (ISPs) began to emerge in the very late of the 1980s, and the first stage of the technology foundation of Internet, ARPANET, was decommissioned in 1990. Limited private connections to parts of the Internet by officially commercial entities emerged in several American cities by late 1989 and 1990, and subsequently the NSFNET was decommissioned in 1995, removing the last restrictions on the use of the Internet to carry commercial traffic (NSFNET, 2019). The telecommunication industry experienced a spectacular rise from early 1997 before shifting into a similarly dramatic decline from mid-2000 until 2003. Equity valuations and capital spending soared and then plummeted, and a flood of initial public offerings turned into a flood of bankruptcy filings. The boom and bust in telecommunications coincided with the boom and bust in the U.S. equity market as a whole and with the dot-com bubble of Internet stocks. The dot-coms received most of the publicity initially, but the telecommunication industry accounts for a much larger share of market capitalization gained and lost than did the dot-coms, however, they are very much related (Couper, Hejkal and Wolman, 2003).
In 2003, the Voice over Internet Protocol (VoIP) was developed. This is a methodology and group of technologies for the delivery of voice communications and multimedia sessions over Internet Protocol (IP) networks, such as the Internet. The terms Internet telephony, broadband telephony, and broadband phone service specifically refer to the provisioning of communication services, such as voice, fax, SMS, and voice-messaging, over the public Internet (FCC, 2019). As widespread usage of mobile telephony and broadband took off, so did the valuation of the telecom companies delivering the service. The industry experienced extreme growth up until being impacted by the financial crisis. Global economic indices fell on average by 58% between October 2007 - when indices peaked, and March 2009 - the bottom of the market. The telecommunication industry indices followed the general economic trend, falling by 49% over the same period. The continuing investment in technology and infrastructure has developed the speed and capacity of networks, and are currently at fifth generation (5G), allowing people to transfer larger amounts of data at higher speeds than ever.

The telecommunication industry within the sector of information and communication technology is made up of all telecommunication companies and internet service providers. Roughly, we can divide the industry into two categories of service providers; namely carriers and resellers. Companies in the carriers category operate or provide access to facilities for voice, data, text, sound, and video transmission through wired, wireless, or satellite networks. Carriers operate in a highly competitive market that includes wireless companies, traditional telephone companies, cable companies, internet service providers, and software and application providers. Market saturation has led to a slowdown in wireless subscriber growth in certain developed regions, driving major carriers to lower their prices to compete. As voice services may increasingly be considered as a commodity, providers may attempt to compete by offering superior customer service or heavily investing in marketing (Dun and Bradstreet, 2019). The resellers purchase network access and capacity from telecommunication carriers and resell wired and wireless telecommunication services to businesses and households. Most major carriers provide network access to resellers on a wholesale basis and also own reseller brands. Demand is driven by consumer spending, growth in business activity, and new technology. The profitability of individual companies depends on efficient operations and good marketing and customer service, and especially large companies enjoy economies of scale in purchasing telecommunication services to resell (Dun and Bradstreet, 2019).
8.2.1 External Factors

The telecom industry was chosen in this analysis because the companies are not reliant on the price of a commodity or a physical asset, rather strictly on their ability to generate good returns from their operations by providing excellent service. Telecom is a capital-intensive industry with high fixed costs. Hence, many telecom companies must finance their capital expenditure with debt to stimulate growth and profit, which often results in high financing costs for the companies. Also, telecom companies have a high depreciation expense due to their networks’ sizeable fixed asset base (Sheffer, 2015). The external factor we sought relevant in this context is, therefore, the price of debt financing represented by the ten-year U.S. Treasury rate.

![Figure 21: (a) Market Capitalization and 10-year U.S. Treasury Rate (b) Market Capitalization and Observations](image)

In the illustrations above we can see how the median market value of the telecom companies has evolved throughout the period. The charts display how the market valuations experienced several peaks and troughs up until the dot-com bubble, and how the market valuations rallied prior to the financial crisis when the industry absorbed the internet revolution. As seen in figure 21a, the ten-year U.S. Treasury rate has had a volatile downtrend throughout the period, meaning debt financing has become much cheaper over the years. This development has been very favorable for the capital-intensive telecom industry. Figure 21b displays the median market values along with the number of companies that were included in the quarterly linear regressions. The number of observations increases substantially in 2005; the same time as we observe the extreme increase in market values. This could be a coincidence, however, considering the number of IT-companies that entered the market and the fact that our data selection has filtered out the firms with negative earnings, it is fair to assume that the number of observations increased as the companies became more profitable.
8.2.2 Multiple Breakdown

In a report covering the telecommunication industry, McKinsey states that “The financial trend in telecommunication industry has been clearly reflected in market expectations and declining multiples” (Boniecki and Marcati, 2016). The technological revolution created high future expectations for investors setting high valuations, while the companies had to invest in order to keep growth up starting the new century. As the figures below illustrate, the multiples maintained high and volatile at the end of the 20th century. As the expectations went up, valuations outgrew the earnings, effectively pushing multiples down. Most multiples saw their lows during the financial crisis, and have slowly and steadily been in an uptrend since then. As PwC stated in their report, they see an industry slowly shifting towards ex-growth as more markets have become developed especially in terms of infrastructure (Sur et al., 2014).

Figure 22: (a) shows EV/EBITDA, ln(EV) and ln(EBITDA) and (b) shows P/B with log-scaled market capitalization and book value of equity.

Figure 22a displays the much-used valuation multiple for industry transactions, EV/EBITDA. The median EV/EBITDA for the telecom industry over the period is 5.37, slightly lower than in the E&P industry. The P/B multiple, however, is quite a lot higher at 2.15 compared to the 1.67 in the E&P industry. This implies that the telecom companies, on average, has been priced at a 215 percent premium on the book value of equity, which would be considered expensive for equities in general. By studying the illustrations, it appears that the multiples both peak in 1999 with an EV/EBITDA close to 15 and a P/B around 6.5, representing extreme levels. Furthermore, the median P/E and EV/Sales for the telecom industry is 16.21 and 1.57, respectively over the period. In comparison, the E&P industry was priced at 14.54 and 3.22 at the same multiples. This implies that the telecom industry is priced higher at the equity multiples, while the E&P industry is priced
higher at the enterprise value multiples. This makes sense considering that both industries are incredibly capital intensive and typically obtain high levels of debt. With the cyclicity and reliance on oil price in the E&P industry, it is logical that investors will require a premium for holding the more risky equity, thus setting a lower valuation for the E&P industry on average.

8.2.2.1 Profitability and Cash Flow

Studying the relationship between the multiples and profitability value drivers in the telecom industry provides a similar picture to that of the E&P industry. While the E&P industry seemed to only have a positive relationship between ROE and P/B, the graphs for the telecom industry appear to display an overall negative relation with exception of the EV/Sales multiple. This is surprising as the derivations from section six discussing the theoretical multiple drivers tell us to expect the opposite.

![Figure 23: (a) P/B and ROE (b) EV/EBITDA and ROIC](image)

Figure 23a displays the quarterly median P/B multiple along with the return on equity, and figure 23b illustrates the EV/EBITDA multiple along with the return on invested capital. The development over time is quite similar for both multiples and metrics and exhibiting high volatility. The P/B multiple shows a somewhat inconclusive relationship to the ROE, while the EV/EBITDA shows tendencies of a negative relationship with ROIC. At first eyesight, it could look like the return on equity has stabilized after the financial crisis; however, the return on equity reaches extreme negative values in 1997 and 2002, stretching the scale. The P/E and EV/Sales multiples graphed against ROE and ROIC and can be found in Appendix 14.2.2.
The derivation of the EV/Sales multiple shows the NOPAT-margin to be a value driver for profitability, and thus we would expect to see a clear positive relationship between the variables in figure 24a. Up until 1999, hypothesis 1.1 seems to hold; however, the margin took a hard hit going into the dot-com event, moving opposite of the multiple. The margin rebounded up until the financial crisis, after which the industry saw a slowly declining NOPAT-margin up until last year. At the same time, the multiple has seen a slight incline since the financial crisis and is currently on its way to seek a higher level from 2018. Even though the relation between the variables has been ambiguous according to the figure, we believe that the significant events at the beginning of the century have caused instability, but that the overall relationship is positive. Higher capital intensity, on the other hand, should theoretically have a negative effect on the EV/EBITDA multiple. However, figure 8.24 illustrates the exact opposite, with the exception of 2001–2007 and the last year. To our surprise, we also found the results to be similar for the reinvestment rate that can be found in Appendix 14.2.2.

8.2.2.2 Growth

According to theory, growth in book value of equity and net earnings are considered as important value drivers for the P/B and P/E multiples, whereas growth in EBIT is considered an important value driver for the EV/Sales and EV/EBITDA multiples. Hypothesis 1.1 seems to hold for all the multiples, but as like the other cases, some relations are difficult to interpret. The positive relation between the P/E multiple and net earnings growth is the most confirming amongst the hypothesis, showing similar trends both characterized with much volatility along the way. As depicted in the illustration below, the EV/EBITDA and the growth in EBIT show the same trends; however, up until 1999 the two variables display an inverse relationship also characterized by much volatility.
Figure 25: (a) P/E and Growth in Net Earnings  (b) EV/EBITDA and Growth in EBIT

As for EV/Sales and growth in EBIT, the hypothesis holds well, showing a strong positive correlation except for 1994-1997. The P/B multiple has the most ambiguous results amongst the multiples. There seems to be a quite strong positive relationship with the growth in book value of equity; however, after 2010 the book value is rebounding down around zero percent in all Q3 numbers. After conducting several investigations in the data set, we suspect that there have been differences in the reporting of Q3 numbers in the non-U.S. companies, as about 50 percent of the firms report a zero growth in book value of equity in the third quarter. The two illustrations can be found in Appendix 14.2.2.

8.2.2.3 Risk

The beta, which is our most prominent measure of risk, shows results that are consistent with the expectations and hypothesis. There is an overall negative relationship between the beta and all multiples, some to a larger extent than others, as in most cases. Similarly, there is a clear difference between the volatility before and after the 2000s', as the volatility in all variables is substantially lower after this point in time. The movements between the multiples and the operating liability risk variable display the same behavior, indicating an inverse relationship, however, with more stability in its fluctuations across time. As for the profit margin risk, the story is different. Surprisingly, the profit margin risk illustrates a strong positive correlation with all the multiples. This can be seen along with the remaining illustrations regarding the risk variables in Appendix 14.2.2.
8.2.3 Summary and Hypothesis Refinement

After a closer analysis of the graphical relationship between the quarterly median multiple values and the identified value drivers in the telecom industry over time, the observations also suggest a revision of the initial hypothesis. As in the E&P industry, the underlining indicates a revision of hypothesis 1.1.

**Hypothesis 1.3**

“There is a ... relationship between the ... variable and the ... multiple in the telecom industry.”

<table>
<thead>
<tr>
<th>Telecom</th>
<th>ROIC/ROIC</th>
<th>Margin</th>
<th>Growth</th>
<th>Capital Intensity</th>
<th>Reinvestment Rate</th>
<th>Beta</th>
<th>Profit Margin Risk</th>
<th>Operating Liability Risk</th>
<th>Financial Leverage</th>
<th>Growth Rate</th>
<th>ROA</th>
<th>10-Year Treasury</th>
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</thead>
<tbody>
<tr>
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<td>Positive</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Positive</td>
<td>Inconclusive</td>
<td>Inconclusive</td>
<td>Positive</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P/C</td>
<td>Negative</td>
<td>Positive</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Positive</td>
<td>Negative</td>
<td>Pos./Neg.</td>
<td>Inconclusive</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EV/EBITDA</td>
<td>Negative</td>
<td>Reg./Pos.</td>
<td>Positive</td>
<td>Negative</td>
<td>Negative</td>
<td></td>
<td>Positive</td>
<td>Negative</td>
<td>Inconclusive</td>
<td>Negative</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EV/Sales</td>
<td>Positive</td>
<td>Inconclusive</td>
<td>Positive</td>
<td>Inconclusive</td>
<td>Inconclusive</td>
<td></td>
<td>Positive</td>
<td>Negative</td>
<td>Inconclusive</td>
<td>Positive</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 27: Refined Hypothesis for the Telecom Industry
9 Linear Regression Analysis

9.1 Introduction and Model Specifications

The descriptive analysis of the two industries has provided us a graphical overview of the relationship between the dependent and independent variables, which encompasses the relationships of the intrinsic multiples. The graphical illustrations enabled us to examine how the fundamental value drivers interact with the multiples. However, in order to obtain an in-depth understanding of how the variables interact with each other and test the identified hypotheses, the thesis will extend the analysis using linear regressions.

The linear regression analysis can quantify the magnitude, the direction and the significance of the relationship between the fundamental value drivers and multiples, referred to as economic and statistical significance, which we believe are adequate to ensure an objective assessment of the reliability and validity of the results. It is also able to provide a model that can value a company, as well as the other companies in the peer group, based on the estimated regression equation and its coefficients. The analysis is designed around the four dependent variables lnP/E, lnP/B, lnEV/EBITDA, and lnEV/Sales, and further analyzed and evaluated in the two peer groups consisting of companies in the E&P and telecom industry. The analysis is also implemented in each available quarter in numerous cross-sectional linear regressions, as well as an overall pooled cross-sectional linear regression for each multiple.

The remaining part of the analysis will also be divided into two main sections. First, we aim to analyze the relationships of the fundamental value drivers that were indicated as influential for the multiples from a theoretical perspective, referred to as the initial model of the multiple. Second, we intend to optimize the initial model of each multiple by using a dynamic approach where we remove or include independent variables based on an economic and statistical assessment of the variable, referred to as the refined models. The refined models will be used thereafter to assess whether a company is over- or undervalued relative to its peers. The results of the analysis will be used to evaluate, discuss and answer the hypotheses presented in the previous sections.

9.1.1 Assessment of the Linear Regression Assumptions

In the following section, we will assess and evaluate the linear regression assumptions of the quarterly cross-sectional linear regression models and pooled cross-sectional linear regression models in
line with the linear regression framework discussed in section four.

9.1.1.1 Linearity

The first assumption of the linear regression model states that the relationship between the dependent- and independent variable is additive and follow a normal distribution. If the relationship between the variables is non-linear or non-additive, equivalent to an exponential or multiplicative relationship, the sample data and the model’s following predictions are likely to be misleading. However, the linear regression framework allows both the dependent and independent variables to be transformed in any way. Therefore, a non-linear relationship requires a logarithmic transformation of the dependent variable, or both the dependent and independent variable, respectively (Nau, 2017).

As a lot of the values of the independent variables are negative, the latter alternative is not ideal in our case, as a logarithmic transformation of both the dependent and independent variables would reduce the sample size dramatically. As negative multiples do not make sense from an economic perspective, the dependent variables in the sample only take on positive values, and we have chosen to transform all of the values of the dependent variables into logarithmic values. By taking the logarithm of the dependent variables, we implicitly assume that the value of the dependent variables grows or decays exponentially as a function of the independent variables, as well as we also reduce the threat of heterogeneity and create a more normal-looking distribution (Nau, 2017; Acosta-Calzado et al., 2010). Lastly, by applying the natural logarithm, small changes in the natural logarithm are equal to percentage changes, which is preferable when interpreting the estimates of the multiples (Nau, 2017). In order to test the assumption of linearity, we have conducted a sample of simple linear regression models and corresponding scatterplots in both the E&P and telcom industry. All sample tests show an additive, linear relationship between the logarithmically transformed dependent variables and independent variables.

9.1.1.2 Homoscedasticity

The linear regression model assumes that the variance of the error term is constant, referred to as homoscedasticity. However, when heteroscedasticity is present, the estimates of the OLS estimator are no longer BLUE. Consequently, the OLS estimator does not yield the estimates with the lowest variance, which leads to bias in test statistics and confidence intervals since the standard errors are biased (Williams, 2015).
Despite the effort to remove or reduce any heteroscedasticity, it still appears to be some heteroscedasticity present in the linear regression analyses. Gujarati (2004) provides some explanations of why heteroscedasticity can arise, specifically related to his study. First, he describes that heteroscedasticity can occur because either people learn and their errors of behavior become smaller over time, or that a growing discretionary income gives people more choices, which increases the variance of the errors since income rise. Second, which is more relevant to the scope of this thesis, is the fact that outliers, skewness, and incorrect data transformation can create heteroscedasticity and affect the results of the linear regression analysis extensively (Gujarati, 2004).

In that sense, the applied logarithmic transformation to the dependent variables had the purpose of solving the two latter, whereas the former issue requires further investigation. Initially, the sample had some significant outliers, and after an extensive study into the sample, we have removed or adjusted some of the flawed observations. However, the fact that the outliers can possess valuable and relevant information, we believe that removing variables without any further specific information is a risk of venturing into data mining and subsequently losing valuable information. In addition, the transformation of the dependent variables imposed in the previous section helps in restoring assumptions and reducing the impact of outliers. Hence, we claim that no additional outliers should be removed based on an extensive examination of the sample, but we acknowledge that this decision may impact the outcome of the linear regression assumptions negatively. In order to detect heteroscedasticity in both the quarterly linear regressions and pooled linear regressions, we have applied the White test. The figures below show the results of the White test on the quarterly lnEV/EBITDA linear regressions in the E&P and telecom industry.

Figure 28: (a) Quarterly White-Tests lnEV/EBITDA, E&P  (b) Quarterly White-Tests lnEV/EBITDA, Telecom
As can be seen, most of the p-values of the quarterly linear regressions for the lnEV/EBITDA multiples are above the significance level. In such cases, the White test indicates that the quarterly linear regressions are subject to homoscedasticity, and similar patterns can be seen in the other multiples displayed in Appendix 14.3. Although the results of the quarterly linear regressions look satisfactory, the results of the pooled linear regressions show another picture. The figure below shows the results of the pooled linear regressions of all the transformed multiples in both industries.

<table>
<thead>
<tr>
<th>POOLED LINEAR REGRESSIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TELE</strong></td>
</tr>
<tr>
<td>WHITE TEST</td>
</tr>
<tr>
<td>P-VALUE</td>
</tr>
<tr>
<td><strong>E&amp;P</strong></td>
</tr>
<tr>
<td>WHITE TEST</td>
</tr>
<tr>
<td>P-VALUE</td>
</tr>
</tbody>
</table>

Figure 29: Pooled Linear Regressions, White-Tests

As opposed to the quarterly linear regressions, all the null hypotheses of the White tests in the pooled linear regressions are rejected. As the pooled linear regressions are based on the entire period, seasonal patterns in the data could be a common source of heteroscedasticity in the errors. We therefore also conduct a graphical assessment of the pooled predicted lnEV/EBITDA on its residuals to further assess whether the multiples in the two industries have stable error variances or not.

Figure 30: (a) Predicted lnEV/EBITDA on Residuals, E&P  (b) Predicted lnEV/EBITDA on Residuals, Telecom
The pooled predicted lnEV/EBITDA on its residuals in both the E&P and telecom industry show constant error variance as opposed to the White tests and similar plots for the other multiples illustrated in Appendix 14.3 all find that the variances of the errors are reasonably stable. Nonetheless, as the overall results of the assumption among all multiples are quite ambiguous, we decide to stay cautious. Hence, there are two conventional approaches to deal with heteroscedasticity; one is using heteroscedastic-robust standard errors; the other one is using Weighted Least Squares (WLS). WLS requires knowledge of the conditional variance on which the weights are based. If this is known, which is rarely the case, we apply the WLS as the BLUE estimator. However, as we do not know the conditional variance, we apply heteroscedastic-robust standard errors in the OLS estimation to control for heteroscedasticity (Torres-Reyna, 2007). When heteroscedasticity is present, robust standard errors tend to be more trustworthy. The robust standard errors do not change the coefficient estimates, but only adjust the standard errors, and thus the test statistics will yield reasonably accurate p-values (Williams, 2015).

9.1.1.3 Normality

The third assumption, normality of the error distribution, creates problems when evaluating whether the coefficients of the model are statistically significant or not. Violations of the normality assumption can arise if the distributions of the dependent or independent variables are themselves significantly non-normal, or if the linearity assumption is violated. As underpinned in section four, the normality assumption is of importance when assessing the robustness of the linear model, as well as when constructing confidence intervals for forecasts. However, if the objective of the analysis is to generate predictions and one is willing to assume that the estimated linear model and its coefficients are correct in terms of minimizing mean squared error, the normality assumption is not predominant (Nau, 2017).

We have already pointed out the concerns regarding outliers in the sample, and the suspicions are further confirmed by assessing the normal probability plots of the lnEV/EBITDA multiple in both industries displayed in figure 31a and 31b below.
As the estimation of the linear regression coefficients is based on the minimization of squared error using the OLS estimator, a few significant outliers can have a negative impact on the coefficient estimates. Ideally, the observations on the normal probability plot should fall close to the diagonal trend line if the distribution is normal. However, as the normal probability plots reveal, the distribution follows an S-shaped pattern. This implies that the residuals have excessive kurtosis, which means that there are most likely a few observations on one or both ends that deviate significantly from the trend line. These outliers require close attention, but as we argued in the previous section, removing further observations would be an excessive risk of losing valuable information, and we are aware of the fact that this especially will affect the results of the normality assumption.

Our suspicions are also confirmed by evaluating the Shapiro-Wilk tests from the pooled linear regressions, where all test statistics reject the null hypothesis of normally distributed errors. Despite the grueling results, Nau (2017) explains that large sample sizes will regularly fail the normality tests just with a small deviation from normality. Moreover, according to the central limit theorem,
the sum of an increasing sample size with independent and identically distributed random variables would move towards a normal distribution (Nau, 2017).

In contradiction to our expectations, the above figures of the quarterly Shapiro-Wilk tests relative to the sample size of the lnEV/EBITDA and lnP/E multiple show a different pattern. It can be seen that the normality assumption passes where the sample sizes are small, whereas the normality assumption is rejected, as expected, where the sample sizes are large. The pattern of the two figures is representative of all of the multiples in both industries and can be seen in Appendix 14.3.

However, in such cases where the sample sizes are smaller, it makes it harder to justify a normal distribution according to the central limit theorem. Nau (2017) writes that small sample sizes will typically pass the normality test due to limited power to reject the null hypothesis. Hence, we should be cautious when interpreting the significance levels, and confidence and prediction intervals in events were the sample size is not sufficient. In events where the sample size is sufficient, the results are more robust as we can take the central limit theorem into account. Lastly, real data has rarely errors that are perfectly normally distributed. According to Gujarati and Porter (2009), the normality assumption only becomes of importance when the sample contains less than 100 observations, while Wooldridge (2009) argues that some econometricians use as low as 30 as a sufficient number of observations.

9.1.1.4 Independence of Residuals

The fourth assumption concerning statistical independence of the errors is not of the most considerable importance from a cross-sectional linear regression perspective according to Nau (2017),
but it is a vital assumption when analyzing and discussing the pooled linear regression and central limit theorem.

As can be seen, most of the Durbin-Watson test statistics of the quarterly linear regressions are in the range between 1.5 and 2.5, which are considered as healthy, while test statistics below 1 or above 3 are a particular cause for concern. Although it seems that the errors are statistical independent of each other based on the quarterly linear regressions, the residuals are plotted against the row numbers to assess whether there appears to be any form of systematic under- or overpredictions.

By evaluating the two figures, it seems to be no systematic under- or overpredictions to either of the plots, as the residuals seem randomly distributed around the center line. A similar conclusion can be drawn from the other residuals and row-number plots displayed in Appendix 14.3. Finally, the Durbin-Watson tests of the pooled linear regressions support the conclusion that the residuals
are statistically independent of each other.

![Pooled Linear Regressions, Durbin-Watson Tests](image)

Figure 36: Pooled Linear Regressions, Durbin-Watson Tests

9.1.1.5 Multicollinearity

The last assumption of the linear model concerns multicollinearity, and as all of the figures are derived from the same location, that includes market values, balance sheets, income statements, and cash flow statements, there is most likely multicollinearity present in the sample. Gujarati (2004) writes that the preferred rule of thumb to multicollinearity is to obtain more data, if possible. This can generate more precise estimates, which implies estimates with lower standard errors, as these errors decrease as the number of observations increase. However, the sample contains more or less all exchange-traded companies within the specific industry, and it is therefore not possible to obtain more data.

Another possibility is to drop independent variables that correlate in order to obtain a model with significant coefficients. However, Gujarati (2004) underpins that by dropping variables, we can lose relevant information, which may yield biased coefficient estimates for the remaining independent variables that are correlated with the dropped variable. Yet, we apply the Variance Inflation Factor and consequently remove any indication of severe multicollinearity immediately when running the linear regression models. Although we acknowledge the risk of losing information, we are not especially worried, as most of the collinear variables express similar relationship.

9.1.2 Concluding Remarks on Linear Regression Models and Assumptions

Intending to assess and evaluate how the linear regression models perform when we test for the underlying linear regression assumptions, this section has revealed that non-constant variance of the errors and outliers are the main issues that may flaw the results and conclusions.
In order to deal with these issues, we apply heteroscedastic-robust standard errors in the OLS estimation, we transform all values of the dependent variables into logarithmic values, as well as we have adjusted or removed the most significant outliers in the sample. By doing so, we intend to reduce the threat of heteroscedasticity, non-additivity, and non-normality. We also rely on the central limit theorem in both the pooled linear regressions and quarterly linear regressions, although we stay cautious when interpreting the estimates of the quarterly linear regressions with insufficient sample sizes. Moreover, we acknowledge that all assumptions do not appear to hold for every linear regression models. Consequently, the insights yielded by the linear regression models may be inefficient, biased or misleading as the linear regression models appear to violate some of the assumptions from time to time.

9.2 Linear Regression Analysis of the Intrinsic Multiples

The initial linear regression models are based on the derivation of the multiples made in section six, which yielded the fundamental value drivers of the multiples from a theoretical point of view. The intrinsic multiples are based on value drivers related to profitability, growth, and risk and the in-depth insights of the interactions between the multiples and fundamental value drivers will be further examined in the forthcoming sections by also taking into account the statistical techniques used to deal with the underlying assumptions.

9.2.1 Initial Linear Regression Models, E&P

In the E&P industry, we have conducted quarterly cross-sectional linear regressions from Q1 1986 until Q4 2018, although the time horizon may vary due to the number of observations related to the intrinsic multiple examined, as well as pooled cross-sectional linear regressions over the entire period. The initial linear regression models may be missing some of the earlier identified value drivers, as we remove variables portraying a high degree of collinearity, as well as we apply the one-year growth rate, as opposed to the three- or five year growth rate, where it is appropriate.

9.2.1.1 lnP/B E&P

Model Evaluation and Key Summary Statistics

The lnP/B multiple is regressed on the independent variables beta, growth in book value of equity, ROE, asset turnover risk, growth risk in net operating assets, profit margin risk, and operating liability risk. In figure 37a and 37b, we have illustrated the adjusted $R^2$ together with the quarterly number of observations, as well as the corresponding p-values for the F-tests of the quarterly linear
regression models. As seen, the adjusted $R^2$ has been fairly stable over the period, although it is having a decreasing trend as the number of observations is increasing. Frost (2014) argues that one potential reason for this decreasing trend could be that the increased sample size is forcing the adjusted $R^2$ closer to the “true” explanatory power of the model in relation to the central limit theorem.

![Figure 37: (a) Adjusted $R^2$ on Observations (b) P-Values of F-Tests](image)

In the quarterly linear regression models, the median value of the adjusted $R^2$ is equal to 0.1875. The F-tests are significant in 121 out of 124 quarters, which indicates the number of times the quarterly linear regression models provide a better fit to the data than a model that contains zero independent variables. Likewise, 13 out of 124 quarters display a VIF larger than ten. In the pooled linear regression model with 17,677 observations, the adjusted $R^2$ is equal to 0.0113. The pooled linear regression model has the most observations across the samples and yields a significant F-test, which confirms that the regression coefficients are jointly significantly different from zero.

In the descriptive analysis, we found that the relation between the multiples and value drivers can be volatile, unstable and challenging to uncover at times. Figure 38 displays the intervals of the standard errors, as well as the minimum and maximum levels of the coefficients. The intervals of all the quarterly linear regressions across all multiples and industries show a large dispersion between the minimum and maximum value of the coefficients, where all the coefficients have shifted sign once during the examined period. This indicates an inconsistency in the estimates yielded by the quarterly linear regressions.

In the quarterly linear regressions, the intercept and ROE are statistically significant 105 and 90 out of 124 quarters, respectively. Comparably, the remaining independent variables range from 27
as the minimum number of significant quarters for the asset turnover risk coefficient to 46 as the maximum number of significant quarters for the beta coefficient. Furthermore, the median values of the independent variables are in line with the expectations outlined in the descriptive analysis except for the growth in book value of equity, which has a negative sign.

![Figure 38: Key Summary Statistics of lnP/B, E&P](image)

Although ROE was highly significant in the quarterly linear regressions, it appears to be just above the 10% significance level in the pooled linear regression model. The pooled linear regression model yields the intercept, as well as the independent variables; growth in book value of equity, and growth risk in net operating assets as statistically significant, even though the economic significance of the two latter is absent.

### Analysis of Selected Coefficient over Time

In extension to the prior remarks, the return on equity stood out as the most statistically significant variable in the quarterly linear regressions but did not yield a statistically significant coefficient in the pooled linear regression model. In line with the expectations, ROE yielded mainly positive values, despite some negative quarters in the quarterly linear regression. First, a positive ROE coefficient implies that investors reward companies with a higher ROE. Second, as seen of figure 39, the estimated quarterly coefficients display a fluctuating, economically significant trend until the 2000s, while the fluctuating trend diminishes afterward until today. Put differently, investors “pay” less for an increase in the return on equity today than they did 19 years ago.
As the E&P industry is heavily dependent on the oil price, we included the variable in figure 39 to see whether the development in the variable could explain the diminishing economic significance of the return on equity. Interestingly, the economic significance of the coefficient drops significantly as a result of the prevailing oil price environment seen from the late 1990s. Hence, we could argue that the higher oil price environment has contributed to a rotation away from accounting measures in terms of how much investors are willing to pay for them. The p-values of the t-stats seen in figure 39b also confirm the observation. The figure displays a pattern where the ROE coefficient is statistically significant when the oil price starts to rise to higher levels, and the relationship between the return on equity coefficient, representing the economical significance of the variable, and oil price becomes more negatively significantly robust from that point in time.

The findings suggest, at least for the last 19 years and when we adjust for a simultaneous change in the other independent variables, that investors are paying less for an increase in return on equity in an environment where the oil price is surging. An oil price hike also seem to increase the statistical significance of ROE as well as decrease its economic significance.

**Trend Summary of All Regression Coefficients**

In Figure 40, we have illustrated the evolvement of the economic and statistical significance of the coefficients over the entire period for all independent variables in the quarterly linear regressions, as well as the corresponding trend in the median industry levels examined in section eight. Similarly to the ROE coefficient, the overall trend of the coefficients is that the economic significance diminishes after the oil price starts to rise against its all-time-high level of 140 USD/Barrel. On the other hand, the trend of the corresponding p-values is not as apparent as for the ROE coefficient, although it is still present for some of the coefficients. Hence, the inferences made for the ROE coefficient may
also be representable for the other coefficients, which states that investors in the last 19 years have been less focused on fundamental measures, and consequently more concentrated on other factors such as the development in the oil price.

Figure 40: Trend Summary of lnP/B Coefficients, P-Values, and Industry Median Values

9.2.1.2 lnP/E E&P

The lnP/E multiple in the E&P industry is regressed against beta, growth in net earnings, return on equity, asset turnover risk, growth risk in net operating assets, profit margin risk and operating liability risk. Similar to the lnP/B multiple, the quarterly linear regressions are characterized by a falling adjusted $R^2$. The illustrations below confirm that there is a high correlation between the number of companies in the sample and the oil price. In particular, the figure below displays a falling sample size in 2014, the same year that the oil price collapsed. At the same time, the adjusted $R^2$ shoots back up to the same level it had in the early 2000s. This indicates that there is a high correlation between the number of companies in the sample and the oil price, as well as that the number of observations is closely related to the explanatory power.

The median adjusted $R^2$ over the period for the quarterly linear regressions is 0.0591, while the pooled linear regression model with a total of 9,753 observations yields 0.0024, in which both are at the lower end of the scale across all multiples in both industries. The F-tests show significant joint coefficients in a total of 111 out of 124 quarters, which is promising for our model, as well as the high F-test in the pooled linear regression model further confirms the high significance rate.
After removing the independent variables that caused much of the multicollinearity, we were left with a total of 20 out of 124 quarters that displayed a VIF larger than ten. Although we could have removed additional independent variables, there was much inconsistency in which independent variables that exhibited multicollinearity in the different quarters, and twelve of the quarters were between 1988 and 1991. Hence, we kept more independent variables despite might causing some multicollinearity in the first three years.

In the quarterly linear regressions, the intercept, along with the coefficients of profit margin risk and ROE are the most statistically significant throughout the period with 115, 52, and 51 significant quarters, respectively. Looking at the minimum and maximum values of the coefficients, we can also see that the same variables appear to reach the most extreme values in terms of economic significance. Moreover, neither the coefficient of profit margin risk nor ROE has the expected sign suggested by theory, but they are somewhat more consistent with our assessment of the correlation between the multiple and variables in the descriptive analysis.

In the pooled linear regression model, the results are slightly different in terms of significance. The most prominent amongst the variables, after the intercept, is the profit margin risk. The most considerable difference between the pooled and quarterly linear regressions is the ROE coefficient which now proves insignificant both in economic and statistical terms. Moreover, the coefficient of the growth risk in net operating assets and profit margin risk is statistically significant but does not carry a strong economic significance on the dependent variable in the pooled linear regression model.
Analysis of Selected Coefficients over Time

In the most prominent independent variables in the quarterly linear regressions, namely profit margin risk and ROE, we observe that the median coefficients are in contradiction to economic theory although the positive coefficient of the profit margin risk was somewhat indicated by the descriptive analysis. However, it should be noted that both the economical and statistical significance of the two coefficients are moderate in comparison to other prominent variables. As opposed to the lnP/B multiple, the ROE coefficient takes on almost solely negative values until the first oil price rally in the time frame of the analysis, and after that loses all its economic significance similar to the ROE coefficient in the lnP/B multiple. The coefficient of the profit margin risk has a slower and steadier decay over the period, slowly losing its economic significance. This undermines our suspicions that fundamental accounting metrics have become less of an indicator for investors as the oil price has surged.

Figure 42: Key Summary Statistics lnP/E, E&P

Figure 43: (a) ROE Coefficient on Oil Price  (b) PMR Coefficient on Oil Price Over Time
**Trend Summary of All Regression Coefficients**

Figure 44 displays a graphic overview of the movement of the independent variables coefficients, p-values, and median industry values over the period. As it appears from the illustration, all of the variables have higher coefficients in the first half of the period, further undermining our suspicions. Furthermore, the shifting coefficients confirm the interpretations of the variables in the descriptive analysis, where it was found difficult to uncover clear relations between many of the fundamental value drivers and multiples, and much volatility was present.

![Figure 44: Trend Summary of lnP/E Coefficients, P-Values, and Industry Median Values](image)

**9.2.1.3 lnEV/EBITDA E&P**

**Model Evaluation and Key Summary Statistics**

The lnEV/EBITDA multiple is regressed on the independent variables beta, ROIC, growth risk in net operating assets, capital intensity, reinvestment rate, growth in EBIT, tax, profit margin risk, and operating liability risk. The adjusted $R^2$ represents a reasonably stable pattern until it significantly drops in the last quarters of 2005 before it subsequently alters into a stable pattern relative to the number of observations. The median adjusted $R^2$ of the quarterly linear regression equals 0.1435, and the multiple has the lowest median standard error of all multiples in the E&P industry equivalent to 1.1655. The F-test is significant in 118 out of 124 quarters, indicating the joint significance of the coefficients in most of the quarterly linear regression models. In the pooled linear regression model with 10,870 observations, the adjusted $R^2$ is equal to 0.0478 with jointly significant independent variables and still the lowest standard errors in the E&P industry.
In the quarterly linear regressions, the independent variable with by far the most statistically significant coefficient is the capital intensity with 94 out of 124 quarters, while the intercept is statistically significant in 98 out of 124 quarters. Economically, the operating liability risk is the only coefficient that expresses the actual theoretical sign of the median coefficient, whereas the coefficients of beta, ROIC, capital intensity, growth risk in net operating assets, and profit margin risk are opposite to what is suggested by theory. However, except for the capital intensity, the statistical significance of all these variables is limited. The remaining coefficients are more or less equal to zero.
The pooled linear regression model yields the coefficients of the intercept, capital intensity, growth in EBIT, profit margin risk, and operating liability risk as statistically significant, and the signs are similar to the median coefficients in the quarterly linear regressions.

**Analysis of Selected Coefficient over Time**

As the most economical and statistically significant coefficient of the quarterly linear regressions, an interesting aspect for the coefficient of the capital intensity is the positive sign which is opposite to what is suggested by theory. This is also found to be true for the pooled linear regression model. A higher capital intensity should theoretically have a negative effect on EV/EBITDA, as seen in the derivation of the multiple in section six. Figure 47 displays, except for a few statistical insignificant negative quarters at the beginning of the period and a quarter in 2005, that the coefficient has stayed positive during the examined period. This indicates that investors are applying a higher multiple for companies with higher capital intensity.

![Figure 47: (a) Capital Intensity Coefficient Over Time (b) P-Values of Capital Intensity Coefficient](image)

We also underpinned in section eight of the descriptive analysis that there was no clear indication of a negative relationship between the multiple and capital intensity. An explanation of the positive relationship between the multiple and capital intensity could be as a result of a downward trending industry EBITDA-margin since a falling EBITDA will cause the capital intensity ratio to increase because of relatively fixed depreciation expenses, and thus the multiple to increase if the enterprise value is stable. Lastly, a positive coefficient of the capital intensity may also signal that investors allocate value on the outlook of more oil and revenue in the future, as the capital intensity increases when oil companies invest in more oil reserves and increased oil production.
Trend Summary of All Regression Coefficients

The coefficient of beta is mainly positive but also recognized as statistically insignificant. However, the few quarters the coefficient is negative, it also appears to be the quarters where the coefficient is statistically significant. The coefficient of ROIC fluctuates between negative and positive values at the beginning of the period but is later losing all of its economic significance and rarely statistically significant. Similarly to ROIC, the growth risk in net operating assets shifted between negative and positive values in the 1990s, before altering into being economical insignificant and seldom statistical significant during the remaining period. Although the reinvestment rate has been highly fluctuating, the coefficient loses its economic significance in the later periods, and are seldom able to pass the test of statistical significance.

The profit margin risk displays a significant economic significance during the entire period, and after mainly positive values in the 1990s, the coefficient fluctuates between negative and positive values in the later period, yet the coefficient is being subject to statistical insignificance in the majority of the quarters. Despite the statistical insignificance in the quarterly linear regressions, the coefficient yields economic and statistically significant results in the pooled linear regression model. The coefficient of the operating liability risk has been volatile and lost most of its economic significance during the last 15 years, but interestingly seems to be statistical and economically significant when the coefficient is negative as suggested by theory, which is also confirmed by the pooled linear regression model. Lastly, the coefficients of growth in EBIT and tax do not display any particular pattern and subject to statistical and economic insignificance throughout most of the period.

Figure 48: Trend Summary of lnEV/EBITDA Coefficients, P-Values, and Industry Median Values
9.2.1.4 lnEV/Sales E&P

The lnEV/Sales multiple is regressed against beta, return on invested capital, growth risk in net operating assets, reinvestment rate, growth in EBIT, tax, NOPAT-margin and operating liability risk. The quarterly linear regressions yield an adjusted \( R^2 \) equal to 0.1955, which is the highest median adjusted \( R^2 \) across all multiples in both industries. In particular, the level of the adjusted \( R^2 \) remains satisfactory during the entire period and does not collapse at any point in time as we have seen in some of the other multiples. Additionally, the F-tests of the quarterly linear regressions provide us with the most significant quarters of all the multiples, and only two quarters yield a VIF above ten, which implies a reliable model.

![Figure 49: (a) Adjusted R² on Observations (b) P-Values of F-Tests](image)

Although the quarterly linear regressions provide good results in terms of statistical significance for most of the independent variables, the median values of the coefficients are close to zero and of less economic significance compared to the other multiples. The coefficients of growth in EBIT and operating liability risk have the sign of coefficient that is consistent with theory, whereas the remaining coefficients either have the opposite sign or do not indicate any particular relationship. In the pooled linear regression model with 14,116 observations, we also obtain the model with the highest adjusted \( R^2 \) of all models in the E&P industry equivalent to 0.0487. Similarly to the quarterly linear regressions, most of the coefficients show limited economic significance.
Figure 50: Key Summary Statistics lnEV/Sales, E&P

Analysis of Selected Regression Coefficient over Time

The most prominent coefficient amongst the independent variables in the quarterly linear regressions is the NOPAT-margin. The NOPAT-margin proves itself significant in a total of 111 out of 132 quarters, and the coefficient takes on negative values in both estimations which is not consistent with economic theory. Although economic theory suggest a positive relationship, we are also aware of that earnings in the E&P industry are extremely volatile and their cash flows are often completely reinvested in new assets. Hence, the variation in capital expenditures tend to follow the price of oil, and since the oil price is so volatile, this makes capital expenditures volatile and earnings a sensitive metric for the profitability of the companies in the industry. For example, the descriptive analysis revealed that oil companies were experiencing cost inflation up until the oil price collapse in 2014. In such cases, the companies may experience expanding multiples even though the earnings-margin is decreasing in absence of proper cost management. This implies that investors may use other metrics than earnings to measure the true profitability of companies in the E&P industry. Another explanation of the negative statistical relationship could be related to the conceptualized expansion and contraction pattern illustrated in figure 6. The negative coefficient indicates that investors to some extent are able to look past the current noise and factor in future prospects at the expense of the current state.

The pattern of the coefficient is also similar to the other patterns witnessed in the industry, as the economic significance deteriorates in line with a surging oil price. Furthermore, the p-values of the
coefficient indicate that the extreme negative coefficients appear at the same time as the model cannot reject the null hypothesis that the coefficient is different from zero.

Figure 51: (a) NOPAT-Margin Coefficient on Oil Price Over Time (b) P-Values of NOPAT-Margin Coefficient on Oil Price

Trend Summary of All Regression Coefficients

The trend summary indicates much of the same patterns as we have observed with the other multiples. The coefficients typically take on high values in the early stage of the period, but for the EV/Sales multiple the coefficients take on these values even earlier, as the extreme coefficients appear before 1990 for most of the independent variables.

Figure 52: Trend Summary of lnEV/Sales Coefficients, P-Values, and Industry Median Values
9.2.1.5 Intercept Discussion E&P

At first, we can define the intercept as where the linear regression line crosses the y-axis, and it crosses the y-axis where the mean of the residuals is zero. Therefore, the intercept is adjusting itself to what works mathematically to produce the zero mean and is the mean response when all the independent variables are set to zero. The general perception is that the value of the intercept is meaningless, and it is also referred to as the “garbage collector” of the linear regression model as it serves as a garbage bin for any bias that is not accounted for in the model (Frost, 2013).

Abrams (2012) states that the significance of the intercept is irrelevant in linear regressions of absolute dependent variables, as it does not affect the results of the linear model if the true value of the intercept is close to zero. However, he also claims that the significance of the intercept matters when conducting linear regressions of scaled dependent variables. If we assume all coefficients of the independent variables are zero and the intercept is significant, he argues that the average multiple of the observations is likely to be a valid forecast value since we cannot reject the null hypothesis that the multiple is equal to zero.

Put differently, and remembering that multiples are more likely to reflect the current mood of the market, we assume that if the market assigns a higher multiple to an industry caused by non-fundamental changes, the intercept will be pushed up relative to the previous estimated linear regression line. Oppositely, if the market assigns lower multiples to an industry without any change in fundamentals, the intercept will decrease. Thus, the intercept is picking up new effects that the linear model does not capture. The similar effect could be seen if the fundamentals are increasing (decreasing) and the multiples stay flat, the intercept will decrease (increase). Therefore, it may be fair to assume that the intercept is capturing the market behavior and mood of the market beyond the estimated models. This behavior may also be explained by the elements discussed in section five, where investors seemed to value cyclical companies with a mix of “perfect foresight” and “zero foresight”.

The fact that the mean industry multiple and the intercept most likely will be close to each other when the linear regression line has a low $R^2$ is also an interesting aspect of the estimation. In order to understand the relationship, we have to recall what the $R^2$ is telling us. The $R^2$ is the proportion of variance in the dependent variable that is predictable from the independent variables. Hence, a linear regression line can be flat if the intercept is significant and the coefficients of the
independent variables are insignificant. Thus, the flat linear regression line, primarily represented by the intercept, will therefore almost be equivalent to the mean multiple in the industry.

Figure 53: Trend Summary of the Coefficients and P-Values for the E&P Intercepts

As seen, the common trend of the economic significance of most of the coefficients of the fundamental value drivers can be described as diminishing after a certain threshold. Interestingly, the lnEV/EBITDA and lnEV/Sales intercepts show the opposite trend, and the magnitude of the intercept appears to increase at the same threshold as many of the fundamentals’ coefficients are losing their economic significance. The intercept of lnP/B expresses a similar, but a more fluctuating trend, whereas the intercept of lnP/E shows a fairly stable pattern. The intercepts also show great statistical significance, and the few quarters they exceed the threshold of the critical value are typically at the beginning of the examined period.

By assessing the evolvement of the intercepts and taking the arguments above into account, some interesting patterns have to be further examined. The first observation that comes into mind is that the intercepts of the multiples are picking up the effects of the movements caused by the oil price as it is not accounted for in the initial linear regression models. Figure 54a displays that the intercept of the EV/EBITDA multiple is closely following the fluctuations in the oil price from the middle of the 1990s. The observation is further confirmed by evaluating the p-values for the t-stats of the intercept, where figure 54b shows that the intercept becomes statistically significant at the same time as the oil price starts surging.
The second observation concerns the difference between the intercept and median industry multiple, which seems to decrease in line with a lower adjusted $R^2$. Figure 55 illustrates the intercept relative to the median industry EV/EBITDA multiple and adjusted $R^2$.

Interestingly, the difference between the intercept and the median EV/EBITDA multiple narrows when the adjusted $R^2$ decreases and widens when it increases. The positive relationship is also confirmed when we perform a simple linear regression of the difference between the intercept and median industry EV/EBITDA multiple on the adjusted $R^2$. Similar to the previous results, the relationship clearly sticks together with the movements and magnitude of the oil price and strengthens the observations that investors are weighing the oil price more than decreasing fundamentals captured by the increasing intercept and deteriorating coefficients.
9.2.2 Concluding Remarks in the E&P Industry and Hypothesis Evaluation

After evaluating all multiples in the E&P industry, the findings of both the quarterly linear regressions and pooled linear regression models suggest that there is an unstable relationship between the theoretical fundamental value drivers and the multiples. The unstable relationship concerns both the statistical and economic significance and make it difficult to assign only one conclusion to how the fundamental value drivers affect the multiples over time. However, the analysis has unfolded several interesting aspects related to the drawn hypotheses of the thesis.

At first, we confirmed that the relationship between the fundamental value drivers and multiples are volatile, unstable and difficult to uncover, particularly displayed by the shifting coefficients of all the independent variables examined. As a general observation, the lack of consistency between statistical significance and economic relevance, evidently seen by the moderate magnitude of the coefficients, makes it difficult to interpret any meaningful economic interpretations to most of the independent variables. Moreover, the coefficients are not always depicting the sign suggested by theory, and some take on different signs depending on the multiple examined. For instance, the coefficient of ROE takes on positive values in the lnP/B multiple, whereas it has solely negative values in the lnP/E multiple. Likewise, the median coefficient yielded from the quarterly linear regressions may not have the same sign as the coefficient in the pooled linear regression, illustrated by the coefficient of the profit margin risk in the lnP/E multiple.

Finally, and the most interesting of the findings in this analysis, is the increasing intercept and the diminishing coefficients of the fundamental value drivers observed in all multiples examined. The development is clearly illustrated by the most statistically significant independent variable in the sample, namely the coefficient of ROE in the lnP/B multiple, and can also be seen as a overall trend among the coefficients. The observation is further supported by analysis of the statistically significance of the intercepts in relation to the prevailing oil price environment. Thus, the increase in the intercepts witnessed in the E&P industry can be seen as a manifestation of investors shifting away from fundamental factors included in the model to other unexplained factors, mainly represented by the increase in dependency of the evolvement in the oil price. This also implies that the mean multiple in the industry may be as good at forecasting value in quarters where the model has low explanatory power. All hypotheses concerning the relationship between the fundamental value drivers and multiples in the E&P industry are presented in figure 56.
Figure 56: Hypothesis and Analysis Overview in the E&P Industry
9.2.3 Initial Linear Regression Models, Telecom

In the telecom industry, we have performed quarterly cross-sectional linear regressions from Q2 1990 until Q4 2018, which may vary due to the number of observations of each intrinsic multiple, as well as pooled cross-sectional linear regressions over the entire period. Similarly to the linear regression models in the E&P industry, the initial linear regression models in the telecom industry may also be missing some of the earlier identified value drivers, as we remove variables depicting a high degree of collinearity, and the one-year growth rate is applied for the relevant independent variables.

9.2.3.1 lnP/B Telecom

Model Evaluation and Key Summary Statistics

The lnP/B multiple is regressed on the independent variables beta, ROE, profit margin risk, operating liability risk and financial leverage. The adjusted $R^2$ shows a similar trend as for the multiple in the E&P industry as the explanatory power of the quarterly linear regression models steadily declines with the number of observations. The median adjusted $R^2$ over the entire period is 0.1860, whereas the adjusted $R^2$ in the pooled linear regression model with 14,154 observations only yields 0.0055, which indicates that the pooled linear regression model would yield highly uncertain predictions. The F-test in the pooled linear regression model is highly significant, as well as the F-tests of the quarterly linear regressions yield 100 out of 111 significant quarters.

![Figure 57: (a) Adjusted $R^2$ on Observations (b) P-Values of F-Tests](image-url)

Like in the E&P industry, all the coefficients in the quarterly linear regressions have changed sign during the examined period, and do not represent a stable relationship between the multiple and fundamental value drivers. In the E&P industry, the ROE coefficient was by far the most significant...
coefficient, but this is not the case in the telecom industry. In general, the median values of the coefficients in the quarterly linear regressions are of less economic significance, which may explain why some of the coefficients do not have the expected sign suggested by theory. On the other hand, the financial leverage coefficient stands out as both the most statistical and economic significant independent variable. The coefficient is statistically significant in 86 out of 111 quarters, but we also notice that the coefficient has an unexpected positive median value. In the pooled linear regression model, all coefficients except beta are statistically significant, although there is a lack of substantial economic impact from the variables in general.

Figure 58: Key Summary Statistics of lnP/B, Telecom

**Analysis of Selected Coefficient over Time**

As previously noticed, we expected a negative coefficient for the financial leverage, as leverage typically induces an increased financial risk and consequently a lower valuation of the company as outlined in section 5.2.5 of the theoretical framework. However, if the financial leverage is favorable, which implies that the spread between the required return on operations and the cost of debt is positive, the P/B multiple will be inflated and the positive sign may imply that investors reward companies that exploit favorable leverage. The telecom industry has also historically financed growth by issuing debt, which may be another explanation of why the model indicates an appreciation of leverage.
As discussed in the descriptive analysis, Sur et al. (2014) described a slow shift in the telecom industry towards ex-growth as more markets have become developed especially in terms of infrastructure. The evolvement of the economic significance for the financial leverage coefficient supports this observation, as investors in the recent years have not rewarded the level of financial leverage as much as they did a couple of years ago.

**Trend Summary of All Regression Coefficients**

As the trend for the P/B multiple in the E&P industry was similar among all coefficients, the overall trend of the coefficients for the multiple in the telecom industry is more diverse, although the overall trend is deteriorating. The coefficients do not represent a stable relationship, as most of the coefficients are shifting between positive and negative values.

The beta coefficient is overall of less economic significance, although the most significant negative quarters in 2009 are also supported by statistical significance. The ROE coefficient is shifting between positive and negative values until 2010, where it afterward starts to take on more frequently positive values of higher economic importance. However, this increase in economic significance is not supported by statistical significance. Lastly, the coefficients of the profit margin risk and operating liability risk are also shifting between positive and negative values, before the economic significance of the variables slowly moderates.
9.2.3.2 lnP/E Telecom

The lnP/E multiple is regressed against beta, growth in net earnings, return on equity, growth risk in net operating assets, and profit margin risk. Similar to the lnP/E multiple in the E&P industry, the quarterly linear regressions are characterized by a declining adjusted $R^2$. The metric is decaying from 2002 to 2007, after which it shoots back up, to later go back around zero in 2011, much later than in the E&P industry. The median adjusted $R^2$ for the quarterly linear regressions is 0.1460, considerably higher than in the E&P industry. The adjusted $R^2$ of the pooled linear regression model is also higher, yielding 0.0132. Moreover, the F-tests display good results with significant joint coefficients in a total of 87 of 107 quarters, while 7 out of 107 quarters have a VIF larger than ten.

Initially, the quarterly linear regressions show very similar results for the multiple in the two industries. It appears by figure 62 that the intercept along with the coefficient of ROE is the most significant amongst the independent variables. The intercept has a total of 85 significant quarters,
while ROE is slightly lower with 49 out of 107 significant quarters. Yet, the pooled linear regression model does not provide any meaningful economic insights nor statistical significance for the ROE variable. While the intercept yields great economic and statistical significance, the independent variables only provide economic significance when no statistical significance is present and vice versa.

Figure 62: Key Summary Statistics lnP/E, Telecom

Analysis of Selected Regression Coefficients over Time
As pointed out in the literature review and section 8.2.2 in the descriptive analysis, there has been some speculation that investors in the telecom industry have shifted from valuing growth to appreciate returns and profitability to a higher degree. A closer look at the evolution of the significance of the relevant variables could therefore be interesting.

Figure 63: (a) ROE and GNE Coefficients Over Time (b) P-Values of Variables’ Coefficients

It appears by figure 63a that growth had a higher economic significance up until 2003 when the industry embraced the digital revolution, as the coefficient has diminished since then. It also appears that the return on equity has more impact on the multiple, although it does not appear that there
has been a markedly change from growth to return. Both coefficients seemingly have relatively stable p-values. However, it does appear that the coefficient of ROE is more significant over the period.

Trend Summary of All Regression Coefficients

It can be seen from the trend summary that all of the variables have shifting and volatile coefficients. Hence, it confirms the interpretations of the variables in the industry overview, where it was found hard to uncover clear relations between several of the variables, and considerably volatility was present.

![Figure 64: Trend Summary of lnP/E Coefficients, P-Values, and Industry Median Values](image)

### 9.2.3.3 lnEV/EBITDA Telecom

Model Evaluation and Key Summary Statistics

The lnEV/EBITDA multiple is regressed on the independent variables beta, ROIC, capital intensity, reinvestment rate, tax, and profit margin risk. The adjusted $R^2$ over time diverges from the other multiples, as it drops significantly and subsequently remains low even before the number of observations is starting to increase. The median value of the adjusted $R^2$ in the quarterly linear regressions is also significantly lower than the previous multiples in the industry and equals 0.1160, whereas the F-test is significant in 94 out of 109 quarters. On the other hand, the multiple has the lowest median standard errors of all the quarterly linear regressions. Furthermore, in the pooled linear regression model with 9,678 observations, the multiple has both the lowest standard errors and the highest adjusted $R^2$ across all multiples in both industries equal to 0.0551.
Like the lnEV/EBITDA multiple in the E&P industry, the coefficient of the capital intensity is the most statistically significant in the quarterly linear regressions, which is supported by the economic and statistical significance in the pooled linear regression model. The findings coincide with the industry characteristics discussed in the descriptive analysis of the industry. The remaining coefficients in the quarterly linear regressions, except of the intercept which is statistically significant in 56 out of 109 quarters, can be characterized with low statistical significance and thus their corresponding economic interpretations are limited. However, we notice that the coefficient of the profit margin risk appears highly economically significant, in particular in the pooled linear regression model where it is also statistically significant. As anticipated by the descriptive analysis, the coefficient depicts a positive coefficient in both the quarterly and pooled linear regressions.
**Trend Summary of All Regression Coefficients**

The coefficients in the telecom industry have very similar characteristics to what was observed in the E&P industry. Yet, the beta coefficient changes more rapidly between positive and negative values as well as it has higher economic significance. Furthermore, the coefficient of tax has a clear negative trend in the 1990s, but the economic significance is not supported by statistical significance.

Figure 67: Trend Summary of lnEV/EBITDA Coefficients, P-Values, and Industry Median Values

**9.2.3.4 lnEV/Sales Telecom**

The lnEV/Sales multiple is regressed against beta, return on invested capital, growth risk in net operating assets, reinvestment rate, growth in EBIT, tax, and NOPAT-margin. Similar to the EV/Sales multiple in the E&P industry, the adjusted $R^2$ displays the same falling trend throughout the period, though with lower explanatory power in general. Furthermore, the median quarterly adjusted $R^2$ was found to be 0.1410, as well as the F-tests yielded 111 out of 115 quarters significant and 9 out of 115 quarters had a VIF exceeding ten.

Figure 68: (a) Adjusted $R^2$ on Observations  (b) P-values of F-tests
Like the lnEV/Sales multiple in the E&P industry, the NOPAT-margin was found to be the most prominent coefficient of the independent variables. The coefficient was statistically significant in 81 out of 115 quarters in the quarterly linear regressions, as well as statistically significant in the pooled linear regression model with a negative sign of coefficient. As the E&P industry, the telecom industry has demanded significant amounts of capital expenditure, and in order to keep up with the growth expectations of the market, the earnings may have been neglected by the high expectations and valuations set by investors.

In the pooled linear regression model with 11,352 observations, the adjusted $R^2$ is equal to 0.0044 and yields the intercept, NOPAT-margin, reinvestment rate, growth in EBIT, and tax as statistically significant, although the three latter are close to zero and do not have any meaningful economic insights.

![Figure 69: Key Summary Statistics lnEV/Sales, Telecom](image)

**Trend Summary of All Regression Coefficients**

Judging by the trend summary and knowing the coefficients statistical significance, we can say that the EV/Sales multiple in both industries provide very similar results. The overall trend of the multiple in both industries can be characterized by high statistical significance, low economic significance, and varying signs of the coefficients with most of the impact made at the beginning of the examined period.
9.2.3.5 Intercept Discussion Telecom

At first glance, the intercepts do not capture the same trend caused by an external factor in the same way as seen in the E&P industry. Although the intercepts are of a certain magnitude, the overall trend of the intercepts does not represent a consistent pattern across each other, and it is therefore harder to provide any meaningful interpretations of the economical relevance of the intercepts.

The intercept of the lnP/E multiple is the one that catches the eye, as it has a fairly stable, although seasonal pattern, which could be related to the unstable denominator in the multiple. The intercept has been statistically significant in 85 out of 107 quarters, and the so-called “garbage collector” evidently gathers the additional effects not incorporated by the model, but nonetheless reflect investors’ judgment of the companies. We also remember from section 9.2.1.5 that the intercept will almost be equivalent to the mean multiple in the industry, which is illustrated by the different levels of magnitude of the intercepts seen for instance by the intercepts of the lnP/E and lnP/B multiple. The intercept of the lnP/B multiple has after the middle of the 1990s fluctuated...
around its expected mean industry level of one, only disrupted by some insignificant statistical quarters where the magnitude of the intercept has been more or less equal to zero. The intercept of the lnEV/EBITDA is affected by relatively low statistical significance until 2005 but has afterward shown a slightly seasonal pattern similar to the observed pattern for the intercept of the P/E multiple. Lastly, the intercept of lnEV/Sales also displays a fluctuating seasonal trend, yet the lower quarters are characterized as statistically insignificant, which makes it hard to interpret the exact level of the intercept.

Although the trend of the intercepts in the telecom industry is not as apparent as in the E&P industry, mainly caused by the disruption of the insignificant statistical quarters and the absence of an external factor, the diminishing coefficients of the independent variables and the magnitude of the intercepts indicate that investors focus on other unexplained elements which are not accounted for and not captured by the fundamental value drivers of the multiples.

9.2.4 Concluding Remarks in the Telecom Industry and Hypothesis Evaluation

The findings in the E&P industry suggested that the economic relevance of the fundamental value drivers was diminishing as a result of the increased economic significance related to the development in the oil price. The industry is compared to the telecom industry to evaluate whether the findings in the E&P industry were similar or dissimilar in an industry without any external depending factors. In general, the magnitude of the coefficients for most of the fundamental value drivers was to a greater extent than previously fluctuating between positive and negative values, and did not illustrate any particular patterns. The lack of consistent statistical significance also made it challenging to interpret any meaningful economic interpretations of these variables. Thus, the unstable relationship between the fundamental value drivers and multiples was also present in the telecom industry.

However, the analysis detected significant relationships, and in particular, the coefficients of the financial leverage in the lnP/B multiple, and ROE and growth in net earnings in the lnP/E multiple showed interesting patterns in relation to the examined multiple. The findings suggest that both profitability and growth have been appreciated; however, interpreting the economical significance is difficult due to shifting coefficients.
Interestingly, the findings suggest that the coefficients of the fundamental value drivers seem to diminish in the wake of the digital revolution in the industry. The same transformation has been witnessed in the financial markets, where the development has caused a race to attain data and react to information fastest. Thus, the focus on predicting market movements may has distorted the focus on attaining the information that accurately estimates the assets fundamental value and near-equilibrium price. This may indicate, in the absence of any external factors, that investors in the last decade have had less interest or confidence in fundamental value drivers than they had before. This could be another explanation of the diminishing coefficients and increasing intercepts, and another example of investors shifting away from fundamental factors to other unexplained factors. All hypotheses concerning the relationship between the fundamental value drivers and multiples in the telecom industry are illustrated in figure 72.

![Figure 72: Hypothesis and Analysis Overview in the Telecom Industry](image-url)
9.3 Model Refinement Process

For the remaining part of analysis, we will attempt to optimize the initial linear regression models and create refined linear regression models capable of valuing companies, as well as evaluating whether a company is over- or undervalued relative to its peers. We have chosen to approach the model refinement process based on the framework presented by Boldt et al. (2016). In addition to the fundamental value drivers used in the initial linear regression models, we also obtain a pool of other accounting measures that were not derived from the multiples, as well as variables we considered as possible explanatory contributors to a more accurate multiple valuation.

We follow the framework in a stepwise approach where we first rank each variable based on its statistical significance, followed by an assessment of its economic significance. When adding or subtracting the variables from the model, we check whether the variable is collinear to any of the other variables included in the model. If the variable passes the VIF-test, we include it in the model given that it provides a higher adjusted $R^2$. If the variable is collinear with another variable in the model, the one with the better significance and explanatory power is included. As a final criterion, we check if the inclusion of the variable increase or decrease the AIC and BIC introduced in section 4.3.3. The AIC and BIC values estimate the quality of the model relative to each of the other models; hence, variables lowering these values is preferably included.

9.3.1 Refined Linear Regression Models, E&P

After a thorough refinement process, we are left with a set of refined linear regression models, one for each of the four multiples. The number of variables included in the refined linear regression models is between four and up to seven at the most. The number of observations for the multiple also depends largely on which variables that are included in the linear regression, as some variables contain fewer observations than others. Furthermore, the results of the refined linear regression models displayed in figure 73 are to be compared to the results of the pooled linear regression models to assess whether other independent variables are better able to explain the variations in the examined multiple.

At first glance, the adjusted $R^2$ has improved for all of the four multiples. For lnP/E, lnP/B, lnEV/EBITDA and lnEV/Sales, we now see explanatory powers of 0.0650, 0.0546, 0.0389 and 0.0661, compared to 0.0024, 0.0113, 0.0478 and 0.0487, respectively. Although there is a great
improvement in the adjusted $R^2$ for most of the models, there is still much variation in the dependent variables that are left unexplained. Abrams (2012) states that a low adjusted $R^2$ is very common for linear regressions where the dependent variable is a ratio, and the adjusted $R^2$ could have been higher if one applied a dependent variable in absolute figures instead. The joint coefficient significant tests show a 30x improvement at most and indicate great statistical significance for all four models. The standard deviation of the error terms, however, have not changed much. Consequently, the models will yield fairly wide prediction intervals as there is still much variation left unexplained.

![Image](71x391 to 541x589)

**Figure 73: Refined Linear Regression Models, E&P**

As seen from figure 73, all independent variables are highly statistically significant. Based on the variables that appear significant to the models, it seems like the refined linear regression models prefer earnings-margins and growth variables to the risk variables. Several margin and growth variables have replaced risk variables such as beta, profit margin risk and operating liability risk. This could indicate that investors are more responsive to the profitability and growth aspects of the companies, rather than the risk aspect. The economic significance has increased substantially in general; however, it should be noted that some of the independent variables now are logarithmically transformed, meaning that some coefficients are in relative terms as opposed to absolute terms. The increased economic significance is reflected in the higher adjusted $R^2$ and the lower intercepts than in the pooled linear regressions. It is likely that most of the reduction in the intercepts and increase in adjusted $R^2$ are caused by the inclusion of the risk-free rate and oil price, considering their dominant economical and statistical significance in the models and the similarity between the intercept and oil price observed in the initial analysis.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef</th>
<th>Variable</th>
<th>Coef</th>
<th>Variable</th>
<th>Coef</th>
<th>Variable</th>
<th>Coef</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept**</td>
<td>-1.3493</td>
<td>Intercept**</td>
<td>-1.8152</td>
<td>Intercept**</td>
<td>1.521</td>
<td>Intercept**</td>
<td>-0.731</td>
</tr>
<tr>
<td>In Oil Price***</td>
<td>0.2394</td>
<td>In Oil Price***</td>
<td>0.0035</td>
<td>In Risk-free Rate***</td>
<td>-0.0452</td>
<td>In Oil Price***</td>
<td>-0.2576</td>
</tr>
<tr>
<td>In Risk-free Rate***</td>
<td>0.3475</td>
<td>In Risk-free Rate***</td>
<td>0.7315</td>
<td>In Oil Price***</td>
<td>0.3024</td>
<td>Growth ATQ, Y***</td>
<td>-0.0026</td>
</tr>
<tr>
<td>Growth Net Earnings, Y***</td>
<td>0.0018</td>
<td>Growth Earnings, Y***</td>
<td>0.0013</td>
<td>Tau</td>
<td>0.0013</td>
<td>Growth Revenue, Y***</td>
<td>0.0013</td>
</tr>
<tr>
<td>Net Earnings/Margin***</td>
<td>-0.0151</td>
<td>DE***</td>
<td>0.0019</td>
<td>ROE/Margin***</td>
<td>0.0013</td>
<td>Net Income/Margin***</td>
<td>-0.223</td>
</tr>
<tr>
<td>CFC Margin***</td>
<td>0.0002</td>
<td>CFC Margin***</td>
<td>0.0002</td>
<td>Earnings/Margin***</td>
<td>0.0002</td>
<td>CFC Margin***</td>
<td>-0.3674</td>
</tr>
<tr>
<td>DE***</td>
<td>0.3888</td>
<td>Significance level**</td>
<td>0.01 * 0.05 * 0.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The lnEV/Sales multiple appears to have the highest adjusted $R^2$, as well as the highest joint significance. With the arguments from the intercept discussion in the previous section in mind, we can see that the intercept is reasonably low compared to the lnP/E and lnEV/EBITDA, which is logical as the EV/Sales multiple naturally should have a lower absolute value. Amongst the independent variables, it is undoubtedly the oil price that has the dominant economic significance.

As the model is based on market values of the industry and controls for differences in the independent variables amongst the companies in the sample, a lower or higher predicted multiple than the actual value implies that the market is mispricing the company relative to the peer group. Figure 74 illustrates the models’ prediction of Chevron Corporation’s multiple, along with the actual EV/Sales multiple for Chevron, the oil price, and the industry median multiple over time.

Figure 74 clearly illustrates the close relationship between the median multiple and the oil price. Looking at the predicted value, we can see how the oil price has a dominating economic significance on the dependent variable by how it follows the pattern of the oil price. This also implies that the remaining independent variables cause its deviations from the industry median and oil price. The illustration shows how Chevron has been undervalued on the EV/Sales multiple throughout time with a small exception in 1999.
9.3.2 Refined Linear Regression Models, Telecom

As the refined linear regression models in the E&P industry, the four refined linear regression models in the telecom industry also show great improvement from the pooled linear regression models. The adjusted $R^2$ for the lnP/E, lnP/B, lnEV/EBITDA and lnEV/Sales has improved from 0.0132, 0.0055, 0.0551 and 0.0044 to 0.0778, 0.0227, 0.0628 and 0.0805, respectively. Similarly, the standard deviation has remained close to the same levels, and the F-tests are substantially improved, except for the lnP/B model.

![Figure 75: Refined Linear Regression Models, Telecom](image)

### Table 9.4

<table>
<thead>
<tr>
<th>Variable</th>
<th>ln P/E</th>
<th>ln P/B</th>
<th>ln EV/EBITDA</th>
<th>ln EV/Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adj. R-Squared</td>
<td>0.0778</td>
<td>0.0227</td>
<td>0.0628</td>
<td>0.0805</td>
</tr>
<tr>
<td>F-stat</td>
<td>131.94</td>
<td>75.33</td>
<td>100.94</td>
<td>181.7</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.13</td>
<td>1.13</td>
<td>1.084</td>
<td>1.341</td>
</tr>
<tr>
<td># Observations</td>
<td>5616</td>
<td>10424</td>
<td>10424</td>
<td>10424</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>ln P/E</th>
<th>ln P/B</th>
<th>ln EV/EBITDA</th>
<th>ln EV/Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adj. R-Squared</td>
<td>0.0778</td>
<td>0.0227</td>
<td>0.0628</td>
<td>0.0805</td>
</tr>
<tr>
<td>F-stat</td>
<td>131.94</td>
<td>75.33</td>
<td>100.94</td>
<td>181.7</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.13</td>
<td>1.13</td>
<td>1.084</td>
<td>1.341</td>
</tr>
<tr>
<td># Observations</td>
<td>5616</td>
<td>10424</td>
<td>10424</td>
<td>10424</td>
</tr>
</tbody>
</table>

**Figure 75:** Refined Linear Regression Models, Telecom

By evaluating Figure 75, we find that many of the same independent variables prove themselves both economically and statistically significant and are substantially higher than the pooled linear regression models. Moreover, it appears that it is the profitability and growth variables that explain much of the variance, much like the results seen in the E&P industry. Yet again, it is the lnEV/Sales multiple that has the highest adjusted $R^2$, and a non-fundamental variable represented by the ten-year U.S. Treasury rate appears more economically significant than the others in the model. The intercepts have decreased for three out of the four models, where lnEV/EBITDA is the one that has had a slight increase.

Compared to the E&P models, the intercepts are much higher for the telecom models. This could be because the industry on average is priced at a higher multiple, or due to the fact that the model simply has more of the dependent variable left unexplained, forcing the intercept up to set the mean of the residuals equal to zero. From the quarterly linear regressions, we can calculate that the average median multiples in the telecom industry have been lower than that of the E&P
industry. Hence, it is likely that the lion’s share of the explanatory power in the model lies in the intercept, and that the economic significance of the independent variables has little impact on the dependent variable.

Figure 76: Multiple Valuation lnEV/Sales: AT&T

Figure 76 illustrates the predicted EV/Sales multiple, along with AT&T’s actual EV/Sales multiple valuation and industry median level. As discussed, it is evident from the illustration that the high intercept relative to the independent variables’ coefficients gives the model the same stable prediction over time. Hence, it appears that the intercept is capturing market behavior that is beyond the model. Nevertheless, the model shows that the EV/Sales multiple of AT&T has been overvalued over the entire period of the analysis based on its reported fundamentals.

9.3.3 Concluding Remarks on the Refined Linear Regression Models

The refined linear regression models show increased explanatory power and great statistical significance. The results also confirm the hypothesis regarding the significance of the oil price, and we have been able to set a quantitative measure to the economic significance of the fundamental value drivers, which is surprisingly low. Nevertheless, the results indicate that the models are able to adjust the valuations for fundamental differences amongst the companies and that different value drivers impact the industries and multiples in a varying extent. The initial assumption that the fundamental value drivers would show themselves more prominent in the telecom industry as the industry does not have a dominant external value driver. However, this does not seem to hold based on the little difference in the economic significance of the fundamental value drivers in the
two industries. Despite the improvement in the models, there is much variance left unexplained, reflected in the models’ low adjusted $R^2$ as well as a high standard deviation. This indicates that the models would provide little accuracy in out-of-sample predictions. It is difficult to pinpoint exactly what could cause the low adjusted $R^2$, thus the discussion will contain some reflective thoughts on probable causes.

10 Discussion

The Diminishing Economically Significance of Fundamental Value Drivers

The late 1990s stood out as the turning point for the E&P industry, where the prevailing oil price environment inflated the multiples toward all-time high levels in the industry. We argued that the surging oil price had caused a permanent shift in investors’ behavior displayed in the analysis by deteriorating coefficients of the fundamental value drivers and an increasing intercept over time, primarily triggered by the increased dependency on the evolution in the oil price. This coincides with the findings of Osmundsen et al. (2006) and Chua and Woodward (1994), who found the oil price, company size and proven oil reserves to be substantial predictors of valuation as opposed to fundamental measures.

In the absence of any external depending factors in the telecom industry, the economic significance of the fundamental value drivers has been diminishing as well as the magnitude of the intercept has been relatively stable or increasing during the examined period. The reliability of the results finds support in the studies disclosed in the literature review, as it corresponds with the findings of Acosta-Calzado et al. (2010) observing a similar decrease in the explanatory power and an absence of economic significance. Consequently, we argued that there are likely to be other reasons than only dependencies to external factors affecting the shift away from fundamental factors to other unexplained factors. In that sense, we introduced the developments seen in the financial markets and argued that the focus on predicting market movements had distorted the focus on attaining the information that accurately estimates the assets fundamental value and near-equilibrium price.

In the search of trying to explain the diminishing economically significance of the fundamental value drivers, George Soros explains two cardinal principals of the conceptual framework that applies to financial markets. First, market prices distort the underlying fundamentals to different degrees. This is in direct contradiction to the Efficient Market Hypothesis (EMH), which claims that market
prices reflect all available information about the asset. Second, instead of playing a purely passive role in reflecting an underlying reality, financial markets also have an active role; they can affect the fundamentals that they are supposed to reflect (Soros, 2010). These are the effects we see play out when bubbles generate, and liquidity spirals drain the markets for capital. This concept is also referred to as the positive feedback loop: When the price of an asset appreciates, more investors chase the return which creates a demand pressure. Consequently, the increased value of the collateral makes funding more accessible, generating additional demand. While this phenomenon has always existed, contemporary finance increasingly consists of actors that outsource the calculations and executions of trades to technology, especially algorithms. JP Morgan estimates that quantitative funds and passive investments account for about 60% of market trades, and when markets are volatile, discretionary fundamental investing accounts for as little as 10% of the typical trading volume (Cheng, 2017). As a consequence of how the high-frequency traders and other types of quantitative funds design their algorithms, price distortions such as dumping large sale orders into the market can trigger enormous transactions in a blink of an eye, driving prices far from the assets fundamental value.

Accordingly, Shah (2014) addresses the principal-agent problem and relates it to the financial markets. The principal-agent problem occurs whenever the two actors’ interests are misaligned and monitoring is difficult, and the agent act in a way that does not reflect the principal’s best interest. Shah (2014) underpins that the financial markets are no exception for such vulnerable relationships.

At first, the compensation structures of hedge funds and mutual funds typically consist of a management component that provides revenue in the form of a percentage of assets under management, as well as a performance component related to a share of the upside return. The latter component has often been blamed for incentivizing managers to take on too much risk increasing the speculative component of the stock price. The second aspect relates to the increased tendency for investors to focus on short-term performance rather than the long-term outlook that may represent their best interest. This ”short-termism” indirectly provides managers with an incentive to manage for the short-term. Interestingly, De Long et al. (1990) argued that scholars supporting the EMH in the 1980s had long maintained that markets required only one rational actor to maintain efficiency, as any irrational actor in the market would have their irrational trades countered by the rational actor, who subsequently would collect the gains once market prices returned to fundamental values. However, De Long et al. (1990) stated that when investors face finite time horizons, fully counter-
ing these irrational trades may not be in the investors’ best interest, since rational investors can only take a certain position against irrational movements of the market as they fear that the market might move against them even further and might not correct before they are forced to liquidate.

Additionally, there are several other factors that can cause frictions in the financial markets. For example, there are managed future funds with trend-following investment strategies that are buying securities that have been rising, while shorting those that are falling. Other funds, such as state and pension funds, often have constraints to the leverage in the fund which forces them to buy riskier stocks (high beta) to meet the return requirements. In the introduction to the descriptive analysis we discussed the interest rate as an external factor, and as we saw from the refined linear regression models, the coefficient of the interest rate was a substantial influencer to the multiples. It could also be argued that years of low interest rates and quantitative easing have pushed the price of assets upward, as the government has been a guaranteed counterpart and a buyer of government bonds and forced investors’ capital into riskier assets to yield satisfactory returns. Such frictions in the financial markets cause reinforcing of positive feedback loops, herding of capital and could force liquidation of assets, which all would drive asset prices away from the fundamental values.

In perspective to the findings of this thesis, we argue that the diminishing economic significance may be a result of the increasing willingness of investors to incorporate future prospects rather than historical values, thus abandoning current accounting measures in their appraisal of valuing companies. We also argue that the blossoming of financial actors taking advantage of market frictions and their inability to act rational due to constraints and frictions, rather than act based on fundamental measures, is causing irrational price movements and thus stock prices to deviate from underlying fundamentals in the financial markets.

**Linear Regression Results**

The linear regression analyses have yielded several interesting relationships, but commonly for the analyses is the relatively low explanatory power measured by the adjusted $R^2$. Although the median values of the adjusted $R^2$ of the quarterly linear regressions have been satisfactory, the pooled and refined linear regression models do not represent the same degree of accuracy.

According to Nau (2017), a linear model with a $R^2$ of 10% would have standard errors that are only 5% smaller on average than those of an intercept-only linear model. In such a case, the linear
model would simply predict the mean. However, the linear models are supported by a high degree of significant F-tests as well as statistical and economically significant coefficients, which indicate that the linear models can control for differences in fundamentals across peers as well as providing a better fit to data than an intercept-only model. However, the issue concerning high standard errors and low adjusted $R^2$ really starts to materialize itself when we want to conduct out-of-sample predictions, as the out-of-sample predictions would yield highly uncertain results.

Despite the efforts to not venturing into data mining and consequently losing valuable information, the linear regression models still had presence of outliers, heteroscedasticity, and missing values assuming the logarithmic transformation was correct. We dealt with these issues by transforming all values of the dependent variables into logarithmic values, applying heteroscedastic-robust standard errors in the OLS estimation, as well as we adjusted or removed the most flawed outliers in the samples. The linear regression models still had some minor violation of assumptions, which may have flawed the reliability of the results. However, the low adjusted $R^2$ and economical significance of the fundamental value drivers indicate that other unexplained factors are explaining the variation in the dependent variables that are not accounted for in the linear models.

In order to reveal these unexplained factors and improve the accuracy of the linear models, we suggest that future research should expand their datasets also to include variables explaining future prospects to reflect the modern approach of investors in the financial markets. In such a case, a natural starting point would be to include forward-looking consensus estimates. As the estimated coefficients are quantitative expressions of investors’ behavior, another interesting aspect would be to interpret the coefficients from a behavioral finance perspective to a greater extent. The moderate economical significance of the fundamental accounting measures also suggests that future research should take into account more industry-specific measures such as oil reserves, oil reserve replacement ratios, average return per user and so on.
11 Conclusion

This thesis sought to investigate investors’ behavior across time and how investors appraise fundamental value drivers when using multiples to value companies in the E&P and telecom industry. The fundamental value drivers were obtained from the derivation of the intrinsic multiples to reflect the fundamental value of the companies from a profitability, growth, and risk perspective. By using the linear regression framework suggested by Damodaran (2012a) to control for differences across peer group, the analysis conducted numerous quarterly linear cross-sectional regressions, pooled cross-sectional linear regressions, and refined cross-sectional linear regressions to analyze the relationship between the fundamental value drivers and multiples examined.

The analysis revealed that most of the theoretically expected relationships of the fundamental value drivers in the quarterly linear regressions were ambiguous as the lack of consistency between statistical and economic significance caused unstable relationships and thus made it difficult to interpret any meaningful insights. Nonetheless, the analysis disclosed several coherent statistical and economic significant relationships of the fundamental value drivers explaining the variation in the multiples. In particular, the return on equity was identified as a key value driver for the lnP/B multiple in the E&P industry until the late 1990s, whereas the capital intensity showed its prominence for the lnEV/EBITDA multiple in both industries. It was also disclosed that favorable financial leverage had been a prominent factor for the lnP/B multiple in the telecom industry, as well as the negative coefficient of the NOPAT-margin for the lnEV/Sales multiple in both industries indicated that investors are able to look past the current noise and factor in future prospects.

Nevertheless, the main findings of this thesis suggest that the surging oil price has caused a permanent shift in investors’ behavior displayed in the analysis by falling coefficients of the fundamental value drivers and an increasing intercept over time, largely triggered by the increased dependency of the evolvement in the oil price. The findings in the telecom industry support the trend of diminishing economically significance for the fundamental value drivers but contributes to the thesis by stating that there are other reasons than only dependencies to external factors affecting the shift away from fundamental factors. The refined linear regression models support this observation, yielding the oil price and ten-year U.S. Treasury rate as the most economical and statistical significant variables, increasing the overall explanatory power from the initial linear models. Even though the explanatory power of the models are low, they succeed in differentiating the individual
companies based on a broader set of fundamentals, effectively valuing companies more accurately than applying the industry median.

In conclusion, the thesis suggests that the diminishing economical significance is possibly caused by the highly competitive nature and evolvement of contemporary finance, effectively forcing market participants to seek innovative ways to yield return on their investments. Technology advancement, market inefficiencies, political actions and investors’ attempt to incorporate future prospects are some of the factors we propose could cause distortions in the relationship between the market value and fundamental value of assets.

The findings of this thesis may be valuable for anyone who wants to get a deeper understanding of how fundamental value drivers are valued by market participants in the E&P and telecom industry during the examined period, as well as it could be valuable for market participants searching for an approach to control for differences across peers when evaluating companies.

12 Future Research

We underpinned in the discussion that future research should include variables explaining future prospects of companies rather than historical accounting measures. Accordingly, we suggested that including forward-looking consensus estimates, industry-specific measures, or interpreting the quantitative expressions from a behavioral finance perspective would be apparent starting points. As this thesis examined the E&P and telecom industry, future research should also consider including other industries with different economic characteristics to evaluate whether the findings are similar or dissimilar to the findings of this thesis. Lastly, Knudsen et al. (2017) suggest another approach for controlling for differences across the peer group by using the sum of absolute rank differences (SARD) approach. The SARD approach accounts for an infinite number of proxies for profitability, growth, and risk while remaining independent of industry classifications. The findings of the paper indicate that the SARD approach yields significantly more accurate valuation estimates than the industry classification approach, and should therefore be considered as an alternative to the linear regression framework for future research.
13 Bibliography


14 Appendix

14.1 Data

Figure 77: E&P Equity Screening parameters

Figure 78: E&P Sector Selection
Figure 79: E&P Equity Screening parameters

Figure 80: Tele Sector Selection
Figure 81: E&P Company sample pool pt.1

<table>
<thead>
<tr>
<th>Company Name</th>
<th>Location</th>
<th>Assets Managed</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlantic Resources Inc.</td>
<td>Texas</td>
<td>$5 billion</td>
<td>Largest producer in region</td>
</tr>
<tr>
<td>BP America Inc.</td>
<td>Louisiana</td>
<td>$6 billion</td>
<td>Second-largest in region</td>
</tr>
<tr>
<td>ExxonMobil Corporation</td>
<td>New York</td>
<td>$7 billion</td>
<td>Third-largest in region</td>
</tr>
<tr>
<td>Chevron Corporation</td>
<td>California</td>
<td>$8 billion</td>
<td>Fifth-largest in region</td>
</tr>
<tr>
<td>ConocoPhillips Company</td>
<td>Oklahoma</td>
<td>$9 billion</td>
<td>Sixth-largest in region</td>
</tr>
<tr>
<td>Royal Dutch Shell</td>
<td>Netherlands</td>
<td>$10 billion</td>
<td>Seventh-largest in region</td>
</tr>
<tr>
<td>Total SA</td>
<td>France</td>
<td>$11 billion</td>
<td>Eighth-largest in region</td>
</tr>
<tr>
<td>Eni S.p.A.</td>
<td>Italy</td>
<td>$12 billion</td>
<td>Ninth-largest in region</td>
</tr>
<tr>
<td>Orica Ltd.</td>
<td>Australia</td>
<td>$13 billion</td>
<td>Tenth-largest in region</td>
</tr>
<tr>
<td>Sasol Ltd.</td>
<td>South Africa</td>
<td>$14 billion</td>
<td>Eleventh-largest in region</td>
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</table>

Figure 82: E&P Company sample pool pt.2

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<th>Company Name</th>
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</thead>
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<tr>
<td>Apache Corporation</td>
<td>California</td>
<td>$15 billion</td>
<td>Largest producer in region</td>
</tr>
<tr>
<td>Anadarko Petroleum Corporation</td>
<td>Colorado</td>
<td>$16 billion</td>
<td>Second-largest in region</td>
</tr>
<tr>
<td>Apache Corporation</td>
<td>Louisiana</td>
<td>$17 billion</td>
<td>Third-largest in region</td>
</tr>
<tr>
<td>ONGC Ltd.</td>
<td>India</td>
<td>$18 billion</td>
<td>Fourth-largest in region</td>
</tr>
<tr>
<td>PDVSA SA</td>
<td>Venezuela</td>
<td>$19 billion</td>
<td>Fifth-largest in region</td>
</tr>
<tr>
<td>Statoil ASA</td>
<td>Norway</td>
<td>$20 billion</td>
<td>Sixth-largest in region</td>
</tr>
<tr>
<td>Occidental Petroleum Corporation</td>
<td>Texas</td>
<td>$21 billion</td>
<td>Seventh-largest in region</td>
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<td>Petrobras SA</td>
<td>Brazil</td>
<td>$22 billion</td>
<td>Eighth-largest in region</td>
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<td>Repsol YPF</td>
<td>Argentina</td>
<td>$23 billion</td>
<td>Ninth-largest in region</td>
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<td>Tenth-largest in region</td>
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<td>Italy</td>
<td>$25 billion</td>
<td>Eleventh-largest in region</td>
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Figure 85: Excel’s Bloomberg Add-In - (=BDH() function)

Figure 86: Data Timeline Setup
14.2 Industry and Descriptive Analysis

14.2.1 The E&P Industry

Figure 88: (a) shows EV/EBITDA and growth NOA and (b) shows EV/EBITDA and Asset Turnover
Figure 89: (a) shows EV/EBITDA and EBITDA and (b) shows EV/EBITDA and EV

Figure 90: (a) shows EV/EBITDA and growth EBIT and (b) shows EV/EBITDA and operating liability risk

Figure 91: (a) shows EV/EBITDA and profit margin risk and (b) shows EV/EBITDA and Risk-free rate
Figure 92: (a) shows EV/EBITDA and ROIC and (b) shows EV/EBITDA and reinvestment rate

Figure 93: (a) shows EV/EBITDA and tax and (b) shows EV/Sales and asset turnover

Figure 94: (a) shows EV/Sales and beta and (b) shows EV/Sales and EBIT Margin
Figure 95: (a) shows EV/Sales and EV and (b) shows EV/Sales and growth NOA

Figure 96: (a) shows EV/Sales and NOPAT margin and (b) shows EV/Sales and operating liability risk

Figure 97: (a) shows EV/Sales and Profit Margin Risk and (b) shows EV/Sales and Risk-free rate
Figure 98: (a) shows EV/Sales and ROIC and (b) shows EV/Sales and Sales

Figure 99: (a) shows EV/Sales, EV and Sales and (b) shows market capitalization and risk-free rate

Figure 100: (a) shows P/B and asset turnover and (b) shows P/B and beta
Figure 101: (a) shows P/B and equity and (b) shows P/B and financial leverage.

Figure 102: (a) shows P/B and growth NOA and (b) shows P/B and market capitalization.

Figure 103: (a) shows P/B and operating liability risk and (b) shows P/B and profit margin risk.
Figure 104: (a) shows P/B and risk-free rate and (b) shows P/E and asset turnover.

Figure 105: (a) shows P/E and beta and (b) shows P/E and financial leverage.

Figure 106: (a) shows P/E and growth net earnings and (b) shows P/E and growth NOA.
Figure 107: (a) shows P/E and growth net earnings and (b) shows P/E and growth NOA

Figure 108: (a) shows P/E and market capitalization and (b) shows P/E and net earnings

Figure 109: (a) shows P/E and oil price and (b) shows P/E and ROE
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Figure 110: (a) shows EV/EBITDA and growth NOA and (b) shows EV/EBITDA and Asset Turnover

Figure 111: (a) shows EV/EBITDA and OLR and (b) shows EV/EBITDA and PMR

Figure 112: (a) shows EV/EBITDA and risk-free rate and (b) shows EV/EBITDA and reinvestment rate
Figure 113: (a) shows EV/EBITDA and tax and (b) shows EV/Sales and asset turnover

Figure 114: (a) shows EV/EBITDA and beta and (b) shows EV/Sales and EBIT margin

Figure 115: (a) shows EV/EBITDA and growth EBIT and (b) shows EV/Sales and growth NOA
Figure 116: (a) shows EV/EBITDA and profit margin risk and (b) shows EV/Sales and risk-free rate.

Figure 117: (a) shows EV/EBITDA and ROIC and (b) shows EV/Sales and reinvestment rate.

Figure 118: (a) shows EV/EBITDA and tax and (b) shows EV/Sales, EV and Sales.
Figure 119: (a) shows P/B and asset turnover and (b) shows P/B and beta

Figure 120: (a) shows P/B and financial leverage and (b) shows P/B and growth in book value of equity

Figure 121: (a) shows P/B and growth NOA and (b) shows P/B and operating liability risk
Figure 122: (a) shows P/B and profit margin risk and (b) shows P/B and risk-free rate.

Figure 123: (a) shows P/E and asset turnover and (b) shows P/E and beta.

Figure 124: (a) shows P/E and financial leverage and (b) shows P/E and growth NOA.
Figure 125: (a) shows P/E and operating liability risk and (b) shows P/E and profit margin risk.

Figure 126: (a) shows P/E and risk-free rate and (b) shows P/E and ROE.

Figure 127: (a) shows P/E, market cap and earnings and (b) shows risk-free rate and FL.

14.3 Linear Regression Analysis

Homoscedasticity
Figure 128: (a) Quarterly White-Tests lnP/E, E&P  (b) Quarterly White-Tests lnP/E, Telecom

Figure 129: (a) Quarterly White-Tests lnP/B, E&P  (b) Quarterly White-Tests lnP/B, Telecom

Figure 130:  (a) Quarterly White-Tests lnEV/SALES, E&P  (b) Quarterly White-Tests lnEV/SALES, Telecom
Figure 131: (a) Predicted lnP/E on Residuals, E&P  (b) Predicted lnP/E on Residuals, Telecom

Figure 132: (a) Predicted lnP/B on Residuals, E&P  (b) Predicted lnP/B on Residuals, Telecom

Figure 133: (a) Predicted lnEV/SALES on Residuals, E&P  (b) Predicted lnEV/SALES on Residuals, Telecom

Normality
Figure 134: (a) Normal Probability Plot lnP/E, E&P  (b) Normal Probability Plot lnP/E, Telecom

Figure 135: (a) Normal Probability Plot lnP/B, E&P  (b) Normal Probability Plot lnP/B, Telecom

Figure 136: (a) Normal Probability Plot lnEV/SALES, E&P  (b) Normal Probability Plot lnEV/SALES, Telecom
Independence of Residuals
Figure 140: (a) Quarterly DW Tests lnP/E, E&P  (b) Quarterly DW Tests lnP/E, Telecom

Figure 141: (a) Quarterly DW Tests lnP/B, E&P  (b) Quarterly DW Tests lnP/B, Telecom

Figure 142: (a) Quarterly DW Tests lnEV/SALES, E&P  (b) Quarterly DW Tests lnEV/SALES, Telecom
Figure 143: (a) Residuals lnP/E on Rows, E&P  (b) Residuals lnP/E on Rows, Telecom

Figure 144: (a) Residuals lnP/B on Rows, E&P  (b) Residuals lnP/B on Rows, Telecom

Figure 145: (a) Residuals lnEV/SALES on Rows, E&P  (b) Residuals lnEV/SALES on Rows, Telecom