# BEYOND FUNDAMENTALS

AN EMPIRICAL STUDY OF THEORETICAL VALUE DRIVERS IN THE E&P AND DRY BULK SECTOR

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# ABSTRACT

Det er en bred enighet blant teoretikere og praktikere om at en aksjes virkelige verdi er nåverdien av all fremtidig verdiskapning fra det underliggende selskapet. Markedet er imidlertid ikke begrenset av teorien, og en aksjes verdi i markedet er summen av alle aktørenes forventninger til selskapet, både negative og positive. Denne avhandlingen utforsker skjæringspunktet i mellom teoretiske verdidrivere og markedets prising med fokus på å forstå hvordan investorene vektlegger de fundamentale driverne i sin verdsettelse av selskapene i to sektorer kjent for å være preget av volatile markedsforhold, nærmere bestemt E&P og dry bulk sektoren. Samtidig vil oppgaven forsøke å lage finansielle modeller som kan verdsette selskapene i de respektive sektorene basert på markedets sentiment og vurdering av de fundamentale driverne i sektorene.

Avhandlingen kartlegger den gjeldende verdsettelsesteorien for å danne hypoteser om de forventede relasjonene i mellom pris og verdidrivere, og for å undersøke hypotesene har vi innhentet prisdata og kvartalsvise regnskapstall fra 1980 til og med 2016 for nesten 700 selskaper. Disse dataene er strukturert i en database som benyttes til å gjennomføre deskriptive grafiske analyser og regresjonsanalyser. De grafiske analysene bidro til å skape et overblikk over dataene og fungerte i tillegg som en raffineringsprosess, der vi justerte hypotesene foreslått av teorien til forholdene vi faktisk observerte. Regresjonsanalyser ble gjennomført hvert kvartal med de til enhver tid tilgjengelige datapunktene, slik at stabiliteten i relasjonen mellom pris og verdidrivere kunne vurderes over tid og endringer kunne vurderes i en større kontekst. Det ble også gjennomført analyser med all tilgjengelig data over hele perioden i en samlet stor regresjonsmodell, som på sitt meste inneholdt 12.000 observasjoner.

Resultatene fra de kvartalsvise regresjonene viste at forholdet mellom verdidriverne og markedsmultiplene var ustabile over tid, noe som betyr at den retningen en verdidriver ifølge teorien påvirker markedets prising av et selskap i sektoren vil kunne variere fra en periode til en annen. Tilsvarende var den økonomiske og statistiske signifikansen til verdidriverne også varierende. De samlede regresjonene bekreftet på mange måter våre hypoteser, men driverne var sjeldent statistisk og økonomisk signifikante på samme tid og bekreftet dermed bildet dannet i de kvartalsvise regresjonene. Oljeprisen og fraktrateindeksen var imidlertid både økonomisk og statistisk signifikante drivere for markedsprisen i de respektive sektorene, og det kan derfor konkluderes med at de regnskapsmessige verdidriverne, med noen få unntak, hadde liten innvirkning på prisingen, men at oljeprisen og fraktratene spilte en vesentlig rolle for markedets verdsettelse av selskapene.

Regresjonsmodellene basert på de teoretiske verdidriverne ble raffinert og brukt til å verdsette et selskap fra hver sektor. Selv om modellene har en lav forklaringsgrad, ga de en bedre verdsettelse enn en simpel median/gjennomsnittsbetraktning.

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# INTRODUCTION

Stock prices are mainly determined by supply and demand, and at any stock price there is a fixed supply of shares. Changes in the stock price is therefore caused by the demand for company's shares. According to financial theory, the value of a stock is a function of future value creation, often expressed by fundamentally determinants of value, discounted to present, and as a result there should be a higher demand for stocks with better prospects than the opposite. The challenging part is however that nobody knows for certain what the future will bring. Subjective analysis of the stock leads to different conclusions, some will sell while others will buy, and the position of the demand curve will be determined by the relative strength of the two. Consequently, a stock price is therefore the residual of all the subjective assessments of a stock's prospects.

Since stock prices are at the mercy of human behaviour and expectations, it is not difficult to understand that stock prices of companies in stable and mature industries are less volatile than stock prices of companies in cyclical and shifting industries, mainly because it is "easier" to project the future in these companies. The prospects of cyclical and unstable companies are much more reliant on the evolvement and timing of the cycles, which is something you can only truly assess in past tense. Thus, there is a great uncertainty surrounding these stocks. Some investors will probably put more weight on the current and past conditions, while others put more weight on future unknown prospects or a return to normalised levels. In summary, this leads to fluctuating market prices, as the industry environment is constantly changing and cycles goes through booms and busts.

Both exploration and production (E&P) within the oil industry and dry bulk within the shipping industry, are well known for its instability. These sectors sell generic goods and services, where the price is largely controlled by supply and demand, which forces them to act as price takers, attaching their performance to the volatile nature of the underlying market forces. This dependency creates extensive fluctuations in market values and financial ratios and thus a headache for people trying to forecast their future. Theory provides a general framework and "best practices" on how to value a company, but there exists limited research on how and if the market prices companies according to this theory. Given the instability of the companies in the E&P and dry bulk sector, it should be interesting to investigate if the theoretically fundamentals are important drivers of the market values for these companies and explore the possibility to create a generic model that captures the market's subjective assessment of E&P and dry bulk companies.

# RESEARCH TOPIC

## 2.1 RESEARCH QUESTION & THESIS STRUCTURE

With the above mentioned context in mind, this thesis' ultimate goal and main research topic is to uncover and understand the relationship between fundamentals and market values in the E&P and dry bulk sector across time and cycles, and to create numerous generic relative valuation models able to appraise individually companies in the E&P and dry bulk sector. This thesis will thus try to answer the following research question:

**Research question**

*"How do fundamental determinants of value affect market values of companies within the E&P and dry bulk sector, and is it possible to construct a set of pragmatic multi-linear regression models based on fundamental drivers to value any firm in the respective sectors?"*

First, a literature review is conducted to set the context of our research topic, to present results that may be relevant for our research question and to understand how our thesis is contributing to the existing literature. Then, the thesis will establish a theoretical framework consisting of valuation and regression theory presumed to be conducive to answer the above-formulated research question. The valuation theory is key to understand the factors that theoretically should drive stock prices and how companies ideally should be valued, while the regression theory is crucial to gain an understanding of the theoretical and practical features of a regression model.

All companies regardless of country of domicile and size are included in the analysis. This makes it impossible to compare market values and accounting numbers directly. As a consequence, the next section in the thesis is deriving theoretically relationships between standardized prices and accounting ratios. These theoretically links are the foundation for the initial hypothesis and decisive for the construction of a data base of accounting numbers and standardized multiples.

**Hypothesis 1**

*Fundamental determinants deducted from valuation theory impact the multiples as proposed by the theory*

After a data base is constructed, various multiples and accounting ratios are calculated. The median levels serve as a descriptive summary of the multiples and the fundamentals, and are used for later comparison. Median industry multiples are graphed against their presumed relevant company specific fundamental drivers and the main external industry variable, in order to eyeball the development across time. After investigating and interpreting the graphical relationship between the multiples and the relevant drivers, two hypothesizes are generated and the initial hypothesis are tailored to each sector.

**Hypothesis 2**

*The relationship between the fundamentals and the multiples are unstable across time*

**Hypothesis 3**

*There is a positive relationship between the Baltic Dry Index/oil price and the multiples in the sector*

To test all the hypothesizes above, cross sectional multiple linear regressions of the multiples on the fundamentals are conducted on a quarterly and pooled basis. The assumptions behind the models are carefully disclosed before the regression results are interpreted in-depth, by analysing trends, signs and magnitude of the coefficients and overall explanatory power, which combined, enable us to explain how theoretically fundamental determinants of value affect market values.

The above regression models based on theoretical fundamental determinants are then refined in a dynamic process where we include or exclude variables based on an assessment of multicollinarity, statistical and economic significance and contribution to the overall model fit. After the models are refined, we apply the final regression models to perform predictions on the pricing multiples of a selected company in each of the sectors in every quarter.

**Hypothesis 4**

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

To test the last hypothesis, we compare the multiple from the model to the median multiple and similarly the selected company's fundamentals with the median industry level for the same fundamentals. If the predicted multiples make sense, we can conclude that we have succeeded in constructing a set of pragmatic multi-linear regression models based on fundamentals, that is an improvement to the median multiple, to value any firm in the respective industry.

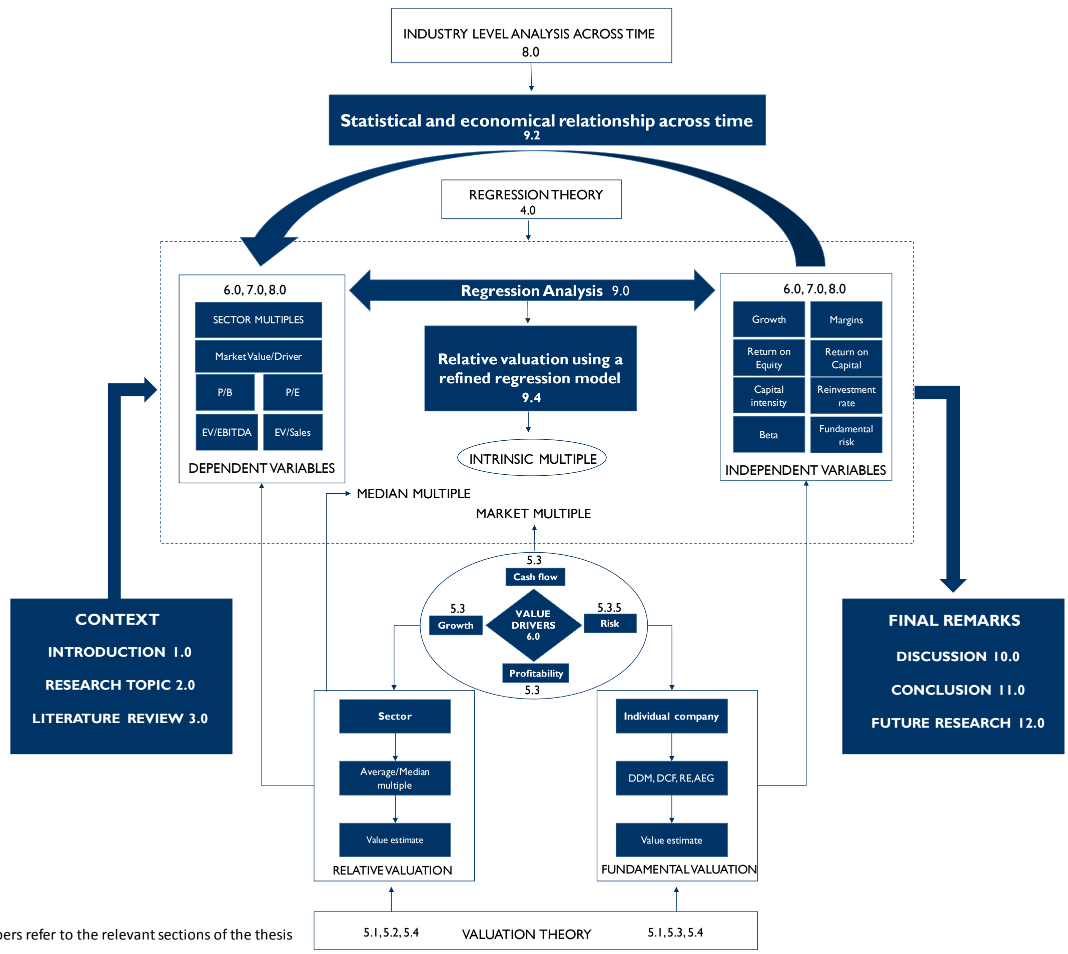
Lastly, we construct a weighted average of the different pricing multiples models with the adjusted R-squared metric to harvest the benefits from several regressions models. This value is tracked against the actual market price of the relevant company to observe how they move about each other.

**Hypothesis 5**

*A weighted adj. R-squared of the multi-linear regression models' multiples can be used to form under- and overvalued signals*

There will be conclusions along the way, but the main conclusion and answers to the research question will be presented in the final remarks section together with a discussion and suggestion of future research on the topic. Figure 2.1.1 provides a cognitive map of the project structure.

**Figure 2.1.1 – Project structure**




*Numbers refer to the relevant sections of the thesis

Source: Own creation

## 2.2 DELIMITATION

The research question and motivation naturally delimitate us to investigate the E&P and Dry Bulk sector. Moreover, we restrict our thesis only to investigate four multiples and their relationship to fundamentals, more specifically the P/B, EV/Sales, EV/EBITDA and P/E multiple. There exists as many multiples as there are accounting numbers, but the chosen multiples are some of the most commonly applied and considered representative for most of the different categories of multiples. We are not restricting the thesis to a specific time period or type of companies within the sectors. However, the time period and number of companies are naturally restricted by the data availability, and limitations will be presented as we go in the data section of the thesis. The investigated fundamental determinants are restricted to the accounting ratios identified in the theory and industry analysis section or those with a close connection to them, and we do not include other variables in the regression analyses. This is to avoid data mining, but it is also due to the difficulty of extracting more "sector specific" data from the financial statements like reserve replacement ratio, reserves and fleet size (deadweight tonnage), even though we admit that these factors possibly have an impact on the fundamental determinants.

The regression model is based on a linear framework, which may or may not be appropriate for the underlying data. Nevertheless, we restrict ourselves from applying other frameworks, i.e. non-linear, to keep the thesis focused. Instead, we are disclosing results from tests of the underlying assumptions, which helps us determine the significance of our results. Moreover, we perform numerous statistical tests to determine the statistical significance of the presumed value drivers and our overall models, which we believe are adequate to ensure that we can assess the reliability and validity of our results. Obviously, there exist numerous statistical methods we could have applied, but our methodological approach and chosen test statistics are in line with methods applied in other research papers and what is proposed by theory. These and other delimitations will be presented as we go in different sections of the thesis.

# LITERATURE REVIEW

## 3.1 GENERAL LITERATURE

After a wide literature search, we could only find a single source that addressed the relationship between fundamentals and market values throughout time and it touched upon the subject only briefly on a market wide basis. Damodaran (2012) investigated the yearly relationship between the P/E-multiple and fundamentals like payout ratio, beta and the historical 5-year growth rate for all listed stocks on the COMPUSTAT database by applying regression analysis each year from 1987-1991 and 2000 to 2011. The yearly regression results expressed a declining R-squared from 1987 to 1991, and coefficients that were dramatically changing over time. In the more up to date market regression, he explains that the coefficient of the expected growth rate yields some insight into how the market is pricing growth. The coefficient is especially high at the peak of the dot-com bubble, which implies that the market was paying a very high price for growth that year, while he finds that the market was paying little for growth in the aftermath of the financial crisis. Damodaran's attempt to interpret the coefficients has been inspirational for our quest to shed light on how fundamentals and market values develop over time in highly cyclical stocks.

Most of the existing research that merge statistical techniques and valuation, mainly focuses on how comparable companies can be identified by fundamentals and which multiple that should be applied to get the most accurate value compared to the prevailing market price, see for example the extensive works of Schreiner (2007) and Liu, Nissim and Thomas (2002). There exists less research on valuation models based on statistical techniques and fundamentals, which potentially can be used to value a large number of companies relative to a sector or the market in a very short time frame. Despite a moderate amount of research on the topic, there are some sources that try to develop or use the regression approach in an attempt to value companies. Damodaran (2012) produces regression functions that express the relationship between the most commonly used multiples and accounting ratios that are considered important drivers for these multiples. These regression functions are then applied in order to perform a relative valuation of companies at a specified point in time. He 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 multicollinarity between financial ratios creates unreliable coefficients and that a linear relationship might not be appropriate. Furthermore, he notices that the basic relationship between the multiples and financial fundamentals is not stable, which can make the predictions from the regression equation untrustworthy for extended periods. Damodaran's final conclusion is thus that a regression analysis has to be viewed as one of many tools in the search for true value.

Li & Li (2013) develop a multiple linear regression model from a sample of 93 Chinese listed companies, where stock prices act as the dependent variable and different financial indicators as independent variables. They conclude that basic financial indicators can explain the stock price effectively. Abrams (2012) has written a detailed paper about regression analysis in the context of valuation. He does not conduct a full empirical analysis, but he provides an example of a company valuation based on a regression of multiples on financial fundamentals in a particular year with a sample of 57 companies. His main goal is to show how to interpret theoretical results from regressions in a business valuation context and how to choose the right explanatory variables, and his article has therefore been motivating for our work.

Acosta-Calzado, Acosta-Calzoda, & Murrieta-Romo (2010) use an impressive set of data when they develop an alternative model to the median multiple approach in order to value a company using either the P/E or the EV/EBTIDA-multiple. Their model is based on public US companies for the years 2000 to 2009, and they create a regression equation for the entire US market each year by taking the logarithm of all variables. They find that the R-squared coefficient do not present high values over the period, but that the F-test indicate that the linear regression model is adequate. In addition, they made regessions for the year 2009 on a sector level since several stock analysts supports the idea that companies in different sectors should trade at different multiples even though they have the same fundamentals. These regression models were used to value each sector by inserting average sector variables in the models, and the results were compared to the simple average sector multiples. Based on this, they conclude that 27 sectors are undervalued and 32 are overvalued. Their model is appealing and convenient, but they neglect to adress the possible multicollinarity problem in the model, nor do they perform any normality or homoscedasticity tests.

In his PhD thesis, Shelbaya (2014) conducts an extensive analysis of multiples and fundamentals, both firm specifics and macro fundamentals, in order to create a model that can perform a cross-sectional relative valuation of any fully-listed company in the Anglo-Saxon and European markets in an identical process. He creates a database comprising ten years of historical company data on Anglo-Saxon and European companies and runs multiple linear regressions of fundamentals on logaritmic transformed value multiples for the period. Shelbaya concludes that he succeded in develop and formulate a structured algoritmich financial model to value any listed company and he detected significant relationships between fundamentals and multiples along the way.

## 3.2 SECTOR SPECIFIC LITERATURE

The previous described literature is broad in its scope since it mainly concentrates on the whole market, and it makes little effort to thorughly investigate spesific industries. However, two relevant journal articles were found covering the E&P sector, while we did not find any relevant research on the dry bulk sector. Chua and Woodward (1994) conducted an econometric valuation test of the P/E-multiple for intergrated US oil companies against dividend payout ratio, net profit margin, asset turnover, financial leverage, beta and interest rate in the period 1980-1990. They fail to uncover any robust relationsip in their data and some of the coeffcients have wrong signs, which inclines them to reject the P/E-model. As a result of this, they test the share price against the same variables as above in addition to the current and future cash flow from operations and proven reserves. This model finds that future cash flow and proven reserves are statistically significant explanatory factors, and thus provides support for the fundamental approach to valuation of oil companies.

Inspired by the increased focus on return on average capital employed (RoACE) among stock analysts and the oil and gas companies, Osmundsen, Asche, Misund, & Mohn (2006) perform yearly linear regression analysis on the relationship between the EV/DACF-multiple and the RoACE based on panel data of 14 major oil and gas companies over the period 1990-2003. They comment that the estimated coeffecients are unstable, unfocused and their t-values vary over time. Their average R-Squared for 13 equations is 0.34, a result they state is “not very impressive”. However, they uncover that there is a positive trend in the estimated RoACE coefficient from 1995. In addition to the yearly regressions, they also do the same regression on the full panel data set to exploit the full power of their data. Despite the increased number of observations, they fail to establish any significant link between RoACE and oil company valuations. On the other hand, they got a robust result expressing that the multiple reacts negative to an increase in the oil price, which, according to Osmundsen et al., is implying that oil and gas companies are priced at mid-cycle oil prices.

### 3.3 CONTRIBUTION TO LITERATURE

This thesis contributes on several levels to the existing literature. As of our knowledge, no previous research has investigated the relationship between fundamentals and multiples on a quarterly basis, which enables us to track investor behaviour more closely and provides a more precise understanding of changes in investor sentiment. We are also looking at a much broader period of time than previous research, going back to the early 80s in the E&P analysis, which implies that we will have more data points in the analysis and thus can capture a greater portion of the volatile environment prevalent in the sectors.

Furthermore, both the dry bulk and E&P sector have not been in the limelight of previous research, so this thesis' analysis is therefore the first to shed light on the prevailing dynamics in the sectors, both in terms of connections between fundamentals and market values and the evolvement across time. Previous work on the oil sector has been limited to integrated oil companies, fewer financial accounting ratios and only one multiple analyzed over ten years, which makes this thesis unique in its perspective on the E&P sector and its analysis of various fundamental determinants specific tailored to explain the development of four different multiples over almost 40 years.

General research on the topic has been more focused on a broad market and more fixated in the predictive possibilities of their models than sectors and the trend in the relationship between the drivers and the multiples. This thesis provides not only new information on how fundamentals have affected the market values of the dry bulk and E&P sector historically, but it also aims to create a valuation model tailored to the specific sectors, which potentially can replace the widespread usage of the median/mean to value or justify values of companies in the sectors.

## REGRESSION THEORY

Faraway (2002) writes that regression-type problems were first applied in the $18^{th}$ century concerning navigation using astronomy. He explains that Legendre developed the method of least squares in 1805, and Gauss demonstrated that the least squares was the optimal solution when the errors are normally distributed in 1809. Today, regression analysis has reached a pivot point in econometrics and it is the prime instrument for analysts and economists when analysing the interaction among two or more variables. Some of the possible regression objectives includes predicting future observations, assessing the relationship between two or more variables and a general description of data structure. These properties make regression analysis a suitable and powerful tool for our quest to understand the interplay between fundamentals and market values and to build valuation models able to capture the mood of the market.

## 4.1 REGRESSION MODEL

Regression analysis can be applied when we want to explain or model the interaction between a single variable $Y$, called the response, output or dependent variable, and one or more predictor-, input-, independent-, covariate- or explanatory variables, $X_1, \dots, X_n$. Faraway (2002) explains that the response variable must be continuous, but that the explanatory variables can take the form as a continuous, discrete or categorical variable. When there is one explanatory variable the analysis is called simple regression, and when there are two or more explanatory variables, it is called multiple regression analysis – this is distinct from multivariate regression, where multiple correlated dependent variables are predicted (Faraway, 2002, s. 13).

### 4.1.2 LINEAR MODEL

Yan & Gang Su (2009) writes that linear regression was the first type of regression analysis to be researched rigorously and broadly applied by practitioners. They argue that this is due to the simplicity of the model that depend linearly on their unknown parameters, which are easier to fit than non-linear models, and an estimator that have easier statistical properties.

The specification of a linear regression model is:

$$\mathrm{Y} = \beta_0 + \beta_1 X_1 + \beta_1 X_2 + \ldots + \beta_n X_n + \varepsilon$$

Here, the dependent variable $Y$, depends on the explanatory variables $X_i$ and the random residual variable $\varepsilon$. The explanatory variables are regarded as deterministic (fixed in repeated samples), while the residuals are random variables, which capture all other factors that influence the dependent variable other than the explanatory variables (Lang, 2016, s. 3). It is thus crucial to determine whether the error term is correlated to the explanatory variables when formulating a linear regression model, as it can alter the slope coefficients (Seal, 1967, s. 11).

$\beta_i$ is an unknown parameter to be estimated from the data, and $\beta_i$ for $i = 1\ to\ n$ is called a slope coefficient, while $\beta_0$ is called the intercept. The elements of $\beta_i$ are interpreted as the partial derivatives of the dependent variable with respect to the various explanatory variables. In a linear model the parameters are entered linearly, which seems rather restrictive, but Faraway (2002) underpins that because the explanatory and dependent variables can be transformed and combined in any way, the model is actually very flexible. He suggests that the variables can be transformed (squared, natural logs etc.) to accommodate for a non-linear relationship. In addition, he writes that truly non-linear models are rarely absolutely necessary, and often emerge from a theory about the relationship between the variables rather than an empirical analysis.

### 4.1.3 ORDINARY LEAST SQUARES

Lai, Robbins & Wei (1978) writes that the ordinary least squares (OLS) is the simplest and most common estimator, due to its conceptually and computationally simple nature. Moreover, OLS estimates are commonly used to analyse both experimental and observational data. This method minimises 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 below:

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

Theory says that this estimator is unbiased and consistent if the residuals have a finite variance and are uncorrelated with the explanatory variables, and it is also efficient under the assumption that the errors have finite variance and are homoscedastic, meaning that the conditional error does not depend on the sequence of the explanatory variable. In an experiment this assumption will generally be satisfied, but with observational data it is difficult to exclude the possibility of an omitted explanatory variable $Z$ that is related to both the observed covariates and the response variable. Lai, Robbins & Wei explain that the existence of such a covariate will generally lead to a correlation between the dependent and explanatory variable, and therefore to an inconsistent estimator of $\beta$.

## 4.2 ERRORS AND REMEDIES

Standard linear regression models with standard estimation approaches rely on several assumptions about the explanatory variables, the response variable and their interaction. Various extensions have been created to allow for these assumptions to be relaxed or in some cases eliminated entirely. However, these extensions make the estimation processes more complex and time-consuming, and may also require more data in order to produce an equally precise model.

The main four assumptions behind the linear regression model is linearity between the dependent and explanatory variables, statistical independence between error terms, constant error variance and normally distributed errors. A violation of any of these assumptions could make the regression model inefficient, and severely biased or misleading. In this section we will focus on the errors that could alters these assumptions, and if applicable, possible detection and remedy tools.

### 4.2.1 HETEROSCEDASTICITY

Heteroscedasticity means that the standard deviation of the residuals depends on the value of the covariate variables and the dependent variable. Lang (2016) writes that textbooks traditionally assumed homoscedasticity (different response variables have the same variance in their errors regardless of the values of the covariate variables) since it simplified both the theory and computations, but that statisticians nowadays normally assume heteroscedasticity, because the homoscedastic assumption very often is invalid when the dependent variables can vary over a wide scale and since this generalisation comes at no extra expense. Furthermore, if the model has heteroskedastic residuals and is miss-specified as homoscedastic, Lang argues that it would cause the standard deviations of the parameter estimates to be inconsistent and make the F-test invalid even though the point estimates of the coefficients remain the same.

## Detecting Heteroscedasticity

In order to determine heterogeneous standard deviation, or when a pattern of residuals breach the homoscedastic model assumptions (error is equally variable around the "best-fitting line" for all points of $X$), it is helpful to look for a "fanning effect" between the residual error and the predicted values (The Pennsylvania State University, 2017). Such a fanning effect means that there is a systematic change in the absolute or squared residuals when plotted against the predicted outcome, i.e. there is a non-constant variance (Minitab Inc, 2016).

The Breusch–Pagan and the White test are two common tests used to test for heteroscedasticity (Pearson Addison-Wesley, 2006, p. 31). Breusch-Pagan tests whether the variance of the errors from a regression is dependent on the values of the independent variables by regressing squared residuals on the covariates (Williams, 2015, p. 4). Thus a significant F-test would indicate that heteroscedasticity is present. The White test is quite similar to Breusch-Pagan test, but the White test allows the explanatory variable to have a nonlinear and interactive effect on the error variance. This test is performed by regressing the squared residual on the predicted dependent variable and the squared predicted dependent variable, and a low $R^2$ and an insignificant F-test will imply that we fail to reject the null-hypothesis about homoscedasticity (Pearson Addison-Wesley, 2006, pp. 32-36).

## Remedies for Heteroscedasticity

### *Reformulate the model*

Lang (2016) expresses that the OLS estimates are much more efficient if the residuals are close to homoscedasticity, so the first and best thing to do is to try and reformulate the model, such as transforming variables, in order to eliminate the heteroscedasticity. He suggests that is often warranted to apply log of the dependent variable if it is positive by nature.

### *Heteroscedasticity-consistent standard errors*

Davidson & MacKinnon (1999) explains how the so-called "sandwich estimator" is an example of a heteroscedasticity-consistent covariance matrix estimator (HCCME). It was introduced to econometrics by White (1980), although there were some precursors in the statistics literature, particularly Eicker (1963, 1967) and Hinkley (1977):

$$\widehat{Var} = (X^T X)^{-1} X^T \widehat{\Omega} X (X^T X)^{-1}$$

If we take the square roots of the diagonal elements of the HCCME equation above, we can achieve standard errors that are asymptotically valid in the presence of heteroscedasticity of unknown form.

The original HCCME above is often called $HC_0$. However, Davidson & MacKinnon state that is not the best available covariance matrix estimator, because least squares residuals tend to be too small. As a result, several better estimators have been developed that inflate the squared residuals slightly in order to offset this tendency. They recommend using a correction factor in which one divides the estimate of the standard error by $(1 - h_t)$ (Davidson & MacKinnon, 1999, s. 200):

$$h_t = X_t(X^T X)^{-1} X_t^T$$

Statistical programs such as Stata uses a much simpler correction, namely the squared root of $N/(N - K)$, but Davidson and MacKinnon (1999) states that Stata's correction is inferior to dividing by $(1 - h_t)$.

### 4.2.2 MULTICOLLINEARITY

Lang (2016) describes multicollinearity, also just known as collinearity, as a situation where two or more covariates in a multiple regression are highly correlated, meaning that one variable can be linearly predicted from the others with a considerable degree of accuracy. This is often labelled imperfect multicollinearity, and if there was an exact linear relationship between two variables, they would be perfectly collinear. Perfect multicollinearity would for example arise when all dummy variables within a category are included in a regression model, because the intercept and the dummy variables would be linearly dependent. In such an event, the collinearity would render OLS estimation impossible (Davidson & MacKinnon, 1999, p. 103).

In the situation of multicollinearity, Lang (2016) writes that the coefficients would have very large standard errors, causing the estimates to change unevenly in response to small changes in the model or the data. However, he also states that the collinearity does not reduce the predictive power or reliability of the model as a whole (at least within the sample data set), it only alters the computations of individual explanatory variables. This means that a regression model with correlated covariates can indicate how well the entire bundle of covariates predicts the dependent variable, but it may not give valid results about any of the individual covariates, or about which variables that are excessive compared to others. Lang nicely states that multicollinearity is not a specification error, just a nuisance making coefficients very imprecise. Lastly, he concludes that these errors decreases as the number of observations increases, so the problem with multicollinearity is in a way equivalent to have few observations.

#### Detecting Multicollinearity

O'brien (2007) suggests that large variations in the estimated coefficients when a covariate is added or removed from the regression could indicate that there is multicollinearity present. Moreover, he explains that insignificant coefficients in the regression model, while the joint null hypothesis (F-test) is rejected and the overall $R^2$ is high, could mean that one or more covariates are correlated. Some authors also suggest to use a formal detection-tolerance formula, such as the variance inflation factor (VIF):

$$VIF = \frac{1}{1 - R_j^2}$$

$R_j^2$ is the explanatory power in a regression of the explanatory variable $j$ on all the other explanatory variables. As a rule of thumb, if the VIF of a variable exceeds 10, which will happen if $R_j^2$ exceeds 0.90, that variable is said to be highly collinear (Gujarati, 2004, p. 366).

Although it is not shared widely, some authors believe that the condition index is the best available multicollinearity diagnostic. The condition index is derived from the eigenvalues as follows:

$$k = \frac{Maximum\ eigenvalue}{Minimum\ eigenvalue} \quad CI = \sqrt{k}$$

The rule of thumb is that a $k$ between 100 and 1000 indicates moderate to strong multicollinearity, and if it surpass 1000 there is serious collinearity. Alternatively, if $CI$ is between 10 and 30 there is moderate to strong multicollinearity, and if it gets over 30, the collinearity turns severe (Gujarati, 2004, p. 362).

### Remedy for Multicollinearity

If multicollinearity is serious, one can either do nothing or follow some rules of thumb. Gujarati (2004) writes that the "do nothing" school of thoughts is well expressed by Blanchard (1967) who stated that multicollinearity is God's will, not a problem with OLS or statistical techniques in general. He explains that Blanchard is really saying that multicollinearity is basically a data shortage problem, and that we sometimes have no choice over the data we have available for empirical analysis. Moreover, Gujarati argues that the existence of multicollinearity does not alter the efficiency of extrapolating the fitted model to new data given that the predictor variables follow the same pattern of multicollinearity in the new data as in the data from the original design.

Gujarati writes that the preferred rule of thumb solution to multicollinearity is to obtain more data (if possible). This can generate more precise parameter estimates, i.e. estimates with lower standard errors, as these errors decreases as the number of observation increases. He also suggests that it is possible to drop one of the explanatory variables in order to produce a model with significant coefficients. But he pinpoints that we can lose information, which could lead to specification bias as well as omitted variable bias, resulting in biased coefficient estimates for the remaining covariates that are correlated with the dropped variable.

### 4.2.3 ENDOGENEITY

Endogeneity is present when the expected value of the residual variable is not equal to zero, because the residuals depend on the value of at least one of the covariates (Lang, 2016, s. 25). According to Lang (2016), this phenomenon arises when the regression equation is structural interpreted, and not when it is applied for prediction. He states that a regression with OLS requires that the residuals are uncorrelated with the explanatory variables, and when this is not the case, OLS will not produce consistent estimates, which underpins the importance of addressing endogeneity. He argues that a positive correlation between the residuals and one of the covariates will overestimate the coefficient, and a negative correlation will underestimate the coefficient. Moreover, he points at sample selection bias, simultaneity, omitted variable bias and measurement errors as possible reasons for endogeneity, which all is addressed below.

#### *Sample selection bias*

Selection bias appears in the data when the probability of being selected to the sample depends on some other criterion than the values of the covariates (Lang, 2016, s. 26). A common situation is survivorship bias, where eliminating a company that stopped trading would create a bias in our data sample, and yielding flawed results.

#### *Simultaneity*

Simultaneity is present when the dependent variable is not only conditional on the covariates, but it also influences one or more covariates, i.e. the cause and effect goes in more than one direction. This is the case if demand is regressed on price, because the effect goes both ways – an increase in price reduces demand, and an increase in demand increases price (Lang, 2016, s. 26).

#### *Omitted variable bias*

An omitted variable bias is when a component of the residual that correlates with some covariate that can be identified, but is not included (Gujarati, 2004, pp. 490-493). Low fuel consumption would for example, ceteris paribus, have a positive impact on the price of a car. Still, if we created a regression with price on fuel consumption, the coefficient would most likely be positive. This is because fuel consumption correlates with some other variable in the residual term, such as engine power, and a high engine power increases both fuel consumption and price. In this case the remedy is simple: include the missing covariate (Lang, 2016, s. 27).

#### *Measurement Errors*

Measurement errors in the explanatory variables cause endogeneity, even though the estimate is unbiased, but measurement errors in the dependent variable just adds a component in the residual, and do not cause endogeneity (Lang, 2016, s. 28).

## 4.3 MODEL EVALUATION

There are several criteria to consider when evaluating how well a regression model serves our purposes, both when choosing among competing models and/or comparing models for forecasting purposes, but also when assessing the quality of an individual model and its parameters (Gujarati, 2004, p. 536). Gujarati (2004) describes several of the criteria in his book on basic econometrics, and three important concepts are summarized in the proceeding sections.

### 4.3.1 HYPOTHESIS TESTNG

The key idea behind tests of significance is to use sample results to verify the truth or falsity of a null hypothesis. A null hypothesis is accepted or rejected on the basis of the value of the test statistic calculated from the data at hand. If we invoke the assumption that $u_i \sim N(0, \sigma^2)$, we can apply the t-test to test a hypothesis about any individual partial regression coefficient. The t-test is computed as:

$$t = \frac{\widehat{\beta_J} - \beta_j^0}{SE(\widehat{\beta_J})}$$

Our objective is to test whether the estimated coefficient $\widehat{\beta_J}$ has any linear influence or explanatory power on the response variable. Thus, we test whether $\widehat{\beta_J}$ is significantly different from zero, which means that $\beta_j^0$ takes on the value of zero. With $n - k$ degrees of freedom we use the t-test to construct a p-value. If the p-value is less than the significance level, statistical significance is attained for the estimated coefficient (Gujarati, 2004, pp. 129, 256).

T-test works well for individual partial hypothesis, but in order to test the joint hypothesis that the coefficients are different from zero simultaneously, we have to use the analysis of variance (ANOVA) technique, which can be demonstrated by computing the F-test as below:

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

Similarly to the t-test, the p-value for the F-test is calculated with $(k - 1)$ degrees of freedom in the numerator and $(n - k)$ degrees of freedom in the denominator to check whether the coefficients are simultaneously under the level of significance. If so, the coefficients are jointly significantly different from zero (Gujarati, 2004, pp. 253, 257).

### 4.3.2 THE $R^2$ CRITERION

$R^2$ , or r-squared, is one of the measures of goodness of fit for a regression model, and it is defined as:

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

The criterion is defined such that $R^2$ takes a value between 0 and 1. The closer it is to 1, the better is the fit, but Gujarati describes several issues with $R^2$. First, it measures in-sample goodness of fit, i.e. how close the predicted response variable is to the actual value in the given sample, and there are therefore no guarantees that it will forecast well for values out of the sample. Second, when comparing two or more $R^2$ , the dependent variables must be the same. Third, $R^2$ will always increase as more variables are added to the model, so there is a temptation to add more variables even though it may also increase the variance of the forecasting error.

As a penalty for including more variables to increase $R^2$, Henry Theil constructed the adjusted $R^2$ as follows (Gujarati, 2004, p. 537):

$$\overline{R^2} = 1 - \frac{RSS/(n-k-1)}{TSS/(n-1)} = 1 - (1 - R^2)\frac{n-1}{n-k}$$

The formula for adjusted r-squared, penalizes the $R^2$ for adding more covariates, and, as seen by the notation, it will always be equal to or less than $R^2$. Unlike $R^2$, $\overline{R^2}$ will only increase if the absolute t-value of the added variable is greater than 1. Consequently, $\overline{R^2}$ is a better measure than $R^2$ and more suitable for comparative purposes (Gujarati, 2004, pp. 536-537).

### 4.3.3 AKAIKE INFORMATION CRITERION

Gujarati also presents the Akaike information criterion (AIC), which carries the idea of penalising the inclusion of covariates further, and the criterion is formulated as:

$$\ln AIC = \frac{2k}{n} + ln\,(\frac{RSS}{n})$$

The $2k/n$ is the penalty factor, where $k$ is the number of covariates (including the intercept) and $n$ is the number of observations. When comparing two or more regressions models, the model with the lowest value of AIC is favoured. Furthermore, it is also useful for not only in-sample, but also out-of-sample forecasting performance of a model (Gujarati, 2004, p. 537).

# VALUATION THEORY

The quoted share price is the most recent price at which the last trade of a stock took place (Harvey, 2011). This price is the residual of all investors subjective opinions on the stock, both positive and negative, and the price at which the market is willing to hold exactly as many shares as there are outstanding shares. There is no universal rule on how to value a stock, but there has been developed general frameworks and different techniques throughout history. It is key to understand the valuation theory in order to recognize the factors that theoretically should affect stock prices and the techniques available to value companies.

## 5.1 VALUATION IN A HISTORICAL CONTEXT

In the mid 1550's the Crown of the English state asked for an average price of twenty-four years' purchase for monastic land (Kew, 1970, p. 98), larger than the twenty years rule first adopted in 1539 (Habakkuk, 1958, p. 364). The years' purchase method valued the yearly rent/yield that could be collected from the properties, and reflected the numbers of years that would pass before the purchase price was recouped. To arrive at the purchase price of the property, they simply multiplied the yearly income stream from the property with the years' purchase. They did not calculate the value by explicitly capitalizing the future rent, these difficulties were at latest overcome in the second decade of the 17th century (Habakkuk, 1958, p. 367), but the rates expressed some opinion about how much the income stream was worth "today".

Harrison (2001) explains that equity shares date back to the incorporation of the Dutch East India Company in 1602, and that shares were actively traded and valued in both London and Amsterdam, long before the so called "South Sea Bubble" in 1720. The early methods for stock valuation were coloured by the extensive historical focus on the yearly yield on properties and the assumption of property value as a function of the stream of rental income. Paid-out dividends from holding securities worked as an equivalent to the rental income on a piece of land, hence Harrison argues that dividends were naturally seen to be the source of yearly return and consequently they became the origin of intrinsic value in the 18th century. Furthermore, the valuation technique applied for land were adopted on stocks (Rutterford, 2004, p. 134), and as a result they used years' purchase multiples to determine the value of the annual dividend payments provided by the securities. Moreover, Harrison describes that tables were published explicitly for providing the calculations of interest payments and present values, and the tables used present value discounting as we would use today. This implies that investors in the early 18th century were able to count for the relationship between the interest rate and asset prices, comparing dividends yields with the profits that could be made if the money was employed differently. The discounting was expressed by the multiplication of the number of "years' purchase" with the annual dividend payment (Harrison, 2001, s. 272), that time's normal P/E ratio. The years' purchase multiple was interfered from the published present value tables, represented by the sum of a dollar of dividend payment in perpetuity discounted at the interest rate.

The importance of dividends continued in the 19th century. There was especially a strong focus on dividend yield and book value when assessing the value of stocks (Rutterford, 2004, p. 142). From the early 20th century Rutterford (2004) declares that the focus, especially in the US., shifted to earnings and investor began to value stocks as a multiple of earnings instead of dividends. She argues that the driver behind the shift was the long and steady growth from the 1st World War until the late 1920s, and the fact that dividends could grow over time, making dividend yields underestimate the true return available from the stock. The 1930s and forward involved the famous "battle" between the value investors and the growth investors.

Value investors calculated the intrinsic value of low P/E stocks and showed that the market mispriced these securities and believed it was foolhardy to value stocks on future growth, while the growth investors advocated that high P/E stocks were an indication of strong growth prospects and claimed that the valuation could be justified by brighter growth prospects than lower P/E-stocks. By the late 1960, the price-to-earnings ratio had become the most common valuation metric (Rutterford, 2004, p. 138).

Even though the recognition of value as a function of all the future dividends from the stock was understood by the investors of the early 18th century, simple multiples continued to be the dominant valuation approach (Rutterford, 2004, p. 141). Multiples accounted for the present value of future dividends, but only in a simplified manner and no explicit forecasting of the future was conducted. Rutterford (2004) postulates that the discounted dividend model first was formalized in modern economic terms in 1938, but did not take off until the 1980s. She points at multiple reasons for this reluctance. Some are the time-consuming job of forecasting cash flows for each company being analysed, market crashes that gave fuel to the value investors and extended the life of multiples and the sensitivity of the model with regards to the dividend input. However, market prices of fast growing stocks and internet companies with no earnings to speak of in the late 1990s could not be explained by simple ratios, forcing analysts to forecast future cash flows and assuming high growth rates (Rutterford, 2004, p. 141). This was the start of an era of the discounted cash flow valuation technique and the approach became the most popular tool at the end of the 20th century (Rutterford, 2004, p. 143). That said, Rutterford (2004) claims that in the calmer markets of the early 21th century, the P/E ratio and the dividend yield have gained reputation once again.

The history reveals the rise of the multiple and the discounted cash flow model, often categorized as relative valuation and fundamental valuation respectively, and these are the most common approaches used today.

## 5.2 RELATIVE VALUATION

Human beings have a tendency to compare and benchmark their own results, accomplishments and abilities relative to others (Richardson, 2016). This urge is transferred to valuation of assets as well. When you are selling your house, you automatically examine the prices of similar houses recently sold in your neighbourhood, and expect to receive the same amount for your own house. Equivalently, you observe housing prices in the same neighbourhood when you want to buy a house, and this alters your price expectations. Likewise, a potential investor investigates how similar companies are priced in the market before he decides what it is worth to pay for the investment. Basically, this is how a relative valuation works - you are valuing assets based on how similar assets currently are priced.

### 5.2.1 STANDARDISED VALUES AND MULTIPLES

Knowledge about the price of a similar asset alone is not sufficient to value an asset on a relative basis. A smaller house in your area will look cheaper than a larger one and a large company with many assets and solid earnings will look more expensive than a smaller start-up in the same industry, hence it is necessary to standardise prices for comparison. This is where the multiples come in handy. The multiples scale the prices of the houses or companies to a common variable, a variable that bear a logical relationship to the observed market price and thus can be seen as a driver of the market value. In other words, you compare how much the market is paying for a unit of the common variable, e.g. the house price per square foot or the company price per dollar of earnings. By doing this, it is possible to compare the prices across the relevant sample despite differences in size and maturity. Standardising of values has given rise to multiples like the price-earnings ratio, price to book value, enterprise value to EBITDA and so on.

### 5.2.2 APPLICATIONS

The multiples are widely used by analysts and investors to value publicly listed companies as well as private companies. In fact, a study from early 2000's concludes that relative valuations in equity research reports outnumbered discounted cash flow valuations almost 10 to 1 (Damodaran, 2006, p. 234). Multiples tend to be used in conjunction with a set of comparable companies, and these comps are supposed to be similar to the company valued with regard to cash-flows, growth potential and risk (Damodaran, 2012, p. 462). The ideal group of comparable companies are identical on these metrics, but it is hard and time consuming to extract a peer group fulfilling this requirement. It is often assumed that companies in the same industry are comparable, even though they may differ in various ways. A multiple is calculated for each comparable company and used to evaluate whether a company is fairly priced given how the comparable companies are priced, and this is usually done by comparing the company's multiple to the average or median multiple in the comparable group. Due to differences among companies in the same sector, it is common to compare the companies on key metrics and modify the multiples accordingly. In addition, some also construct regression models in order to justify why a company should be more expensive/cheaper than the sector or why it should be priced like the typical firm in the industry.

#### Subjective Adjustments

Analysts often make subjective adjustments when they apply a relative valuation to a company. They identify a peer group and calculate the median multiple, and compare it to the company's multiple. In order to understand why it may be cheaper or more expensive than the sector, they calculate key metrics like return on equity, growth rates and margins for each company in the group. If the company shows the same characteristics as the sector averages, it is hard to justify that the company should trade at a higher multiple than the sector, thus the analyst may argue that the company is overvalued relative to the sector. Opposite, if the relevant company has much brighter prospects than the average company, it may deserve a rich valuation. By comparing key metrics across the sample, the analyst can create a convincing story on why the company is cheap/expensive or correctly priced by the market.

#### Modified multiples

Another approach used to control for differences among companies is to modify the multiples used in the valuation. This is usually done by dividing the relevant multiples by a variable which is considered to be the leading determinant for the multiple, e.g. the future growth rate in the price earnings ratio. Modified multiples are premised on the assumptions that the companies in the group are identical on every other metric than the one that is controlled for and a linear relationship between the multiple and the control variable (Damodaran, 2012, p. 463) Since companies often differ on numerous variables, this approach is alone not suitable to tell the full story.

#### Regression of key variables on multiples

By regressing the relevant multiple on numerous company specific variables, it is possible to control for more than one dissimilarity among the firms. This approach works well if your sample of firms is large and the relationship between the multiple and the variables are fairly stable over time (Damodaran, 2012, p. 464). The statistics provided when doing a regression can be used to get a feeling of how well the independent variables explain the multiple in terms of its statistical significance and sign on the coefficient. If the relationship between the multiple and the variables is not linearly, it is also possible to transform the variables in various ways. To assess whether the company is undervalued or overvalued relatively to the sector, the company's values for the independent variables are inserted into the regression function and the subsequent result can be compared to the current multiple.

### 5.2.3 DISTRIBUTIONAL CHARACTERISTICS

Not only is it important to acknowledge the differences between the companies, but it is also essential to know the distributional characteristics of the multiples. Since valuations often are benchmarked against the sector, it is critical to know the "standard" multiple of the typical company as well as the level of a highs and lows in the industry.

#### Average, Median and Outliers

It is easy to think that the standard multiple in the industry is represented by the average multiple of the firms in the industry. However, it is fair to assume that the typical firm is not very well defined by the industry average. In fact, the average will not be a good measure of the central tendency in the sample if the distribution is skewed, since the average will be heavily impacted by large values (Statistics.laerd.com, n.d.). Furthermore, a multiple can mathematically be negative, but from an economic standpoint it does not make sense to apply any meaning to it, since it is not possible to pay less than zero for a company. Coupled with no limitations on the maximum value of the multiple, ignoring the negative values yield a multiple distribution which is naturally skewed towards positive values (Damodaran, 2012, p. 458). This is supported by the fact that all graphical illustrations of the distributions of the most common applied multiples are heavily skewed on the positive side (Damodaran, 2012, pp. 470-544). The impact of this skewness is an average value that is sensitive to outliers. Thus, the median value offers a better indication of the typically firm in the industry, because half of the values fall below the value and half lie above.

### 5.2.4 ADVANTAGES AND DISADVANTAGES

The chosen valuation technique must have benefits that outweigh the cost of applying it, and the cost benefit trade-off of using the method should compare favourably with other alternative techniques (Penman, 2013, p. 76). It is therefore important to understand what is lost by applying the multiple route to a valuation and what is gained.

#### Advantages

One of the main advantages of a relative valuation is its simplicity. The method uses minimal information, often only just a few numbers from the financial statement, and it is way cheaper and quicker to conduct than a full fundamental analysis. Since the valuation is based on how the market is pricing similar companies, a relative valuation will reflect the current mood of the market. As a result, the valuation will be more in line with the investor sentiment and yield higher values than an intrinsic valuation when certain sectors are trending. Moreover, this simplicity enables the investor to value a large sample of companies in a relatively short time frame and with negligible costs, which can be practical when looking for investment opportunities to investigate in more details or when applying a more automatic quantitative investment strategy. Relative valuations are also easier to present as well as sell and defend to clients and customers (Damodaran, 2012, p. 453), as they explicitly rely on fewer subjective assumptions and adjustments than a discounted cash flow analysis.

#### Disadvantages

The strengths of the relative valuation are also its weaknesses. If the valuation only relies on the median multiple in the sector, constructed by dividing the market prices with a simple number from the financial statements (which may be affected by accounting policies), it means that the valuation probably is ignoring a lot of relevant information. Recall that multiples should be different for companies in the same sector as long as the they vary on key characteristics and future prospects. Therefore, in order to conduct a thoroughly relative valuation, it is crucial to control for and consider differences among the firms, and this increase the time consumption of the analysis. Moreover, considerations about growth rates, profitability, return on equity, capital structure, accounting policies etc. across the universe of comparable companies, are often not explicitly stated. Implicit assumptions reduce the visibility of the valuation and conceal the analyst's biases. Coupled with a subjective selection of the comparable companies and the relevant multiples, it is much easier to manipulate the valuation than it is when applying a discounted cash flow valuation with explicitly stated assumptions.

Another key thing to consider is that relative valuations are anchored on the assumption that the market is on average pricing the comparable company universe correct. A value anchored on market prices may be perceived as more objective than other methods, but there is a catch. If the market is mispricing your comparable universe and the market values are inflated, so is your valuation based on the multiples. During the dot-com bubble of the late 90s, prices of tech companies were propelled by speculators to incredible heights (Colombo, 2012). Consequently, relative valuations of tech companies in that period yielded extremely high values, which were justified by skyrocketed multiples of similar companies. Hindsight revealed that the market grossly mispriced these companies and the realization of the error lead to dramatic price corrections.

## 5.3 FUNDAMENTAL VALUATION

Fundamental valuation consists of the models that explicitly forecast future cash flows and discount them back to present. Instead of relying on a multiple founded on standardised prices from similar companies, alternative investments or a multiple established on historical levels, these models focus on firm specifics and prospects – the fundamentals of the companies.

### 5.3.1 THE DIVIDEND DISCOUNT MODEL

The investors in the early 18th century recognized that dividends are the cash flows they get from the firm and the stock's value should therefore be founded on the dividend payments from the company. The dividend discount model offers a formal model applying this concept, and the model is stated as follows:

$$Value\ of\ equity_0 = \frac{d_1}{1+r} + \frac{d_2}{(1+r)^2} + \frac{d_3}{(1+r)^3} + .. + \frac{d_n}{(1+r)^n} + \frac{P_n}{(1+r)^n}$$

The model identifies the sources of cash flows available to an investor in a stock. First, the investor receives dividends, represented by $d_n$ in the formula. Second, the investor can sell the stock at the end of the holding period and receive the price at that time, represented by $P_n$ in the formula. These cash flows are discounted back to the present at a rate appropriate to the riskiness of the cash flows (Damodaran, 2012, p. 323), which is represented by $r$ in the model, and summed to yield the intrinsic value of the stock. The model is theoretically correct, because it is simply the present value of all the future pay offs from the stock. Yet there is an awkwardness to the model, since it tries to find the current price of the stock by forecasting the future price of the stock. To overcome this circularity, the price at the end of the forecasted period, commonly called the terminal value, is often based on the fundamental determinants of value. Since firms are expected to have infinite lives and are characterized as so called "going concerns", the price you can sell the stock for at time $n$ should be the present value of the expected infinite stream of dividends from the company. This is captured by different alternations to the formula, dependent on assumptions about the behavior of the dividend. If it is assumed that the dividend will be constant for the remaining infinite life of the stock, the formula can be expressed as:

$$Value\ of\ equity_0 = \sum_{t=1}^{t=n} \frac{d_t}{(1+r)^t} + \frac{d_{n+1}/r}{(1+r)^n}$$

Thus, the price of the stock at time $n$ is the value of a perpetuity of constant dividend payout for the firm. If it is assumed that the dividend will grow at a stable rate forever, using the Gordon growth model to calculate the price at time n, the formula becomes:

$$Value\ of\ equity_0 = \sum_{t=1}^{t=n} \frac{d_t}{(1+r)^t} + \frac{d_{n+1}/(r-g)}{(1+r)^n}$$

### Advantages and disadvantages

The dividend discount model's main advantage is its simplicity and intuitive logic (Damodaran, 2012, p. 345). It applies an easy and well understood concept, namely that dividends are what you get as a shareholder and the value is naturally assessed by forecasting future dividends. Another advantage is that dividends are easy to forecast in the short run, since they are usually quite stable in this time span (Penman, 2013, p. 114).

However, there are several issues with the model. First of all, dividends do not create value! This is traditional modern finance theory. If a company is paying out a dollar of dividend, the shareholder gets a dollar. But the firm is left with one less dollar, and consequently the value drops with one dollar. The cash flow to the shareholder is made up of dividends and capital gains. The dividend increases the dividend component, but reduces the capital gains component, leaving the shareholder no better off.  Thus, we are left with something called the dividend conundrum, equity value is based on future dividends, but forecasting dividends does not yield an indication of value (Penman, 2013, p. 114). The forecast is not tied to value creation. Secondly, firms that do not pay out dividends or have a very low payout ratio is not equivalent to firms with no value, actually they can be very profitable, plowing back all their earnings into valuable growth projects and be worth a lot. These firms will probably pay out dividends when they reach maturity, but that can take a very long time and it forces the analyst to forecast for long periods, increasing the uncertainty of the forecasts.

### 5.3.2 THE DISCOUNTED CASH FLOW MODEL

The discounted cash flow model solves some of the flaws of the dividend discount model. It is based on the same mathematical paradigm, but it focuses on the investing and operating activities of the firm – features that do create value.

The value of the firm is equal to the value of the debt plus the value of the equity, which is the same as the value of the firm's operating activities. This value is shared between different claimants, namely debtholders and shareholders. According to the present value "rule", the value of any asset is the present value of their expected future cash flows. The value of the equity can therefore be calculated by forecasting future cash flows to the equity holders (the residual cash flows after meeting all expenses, reinvestment requirements, tax duties and interest and principal payments (Damodaran, 2012, p. 13)) and discount them back to present. This resembles the dividend discount model, but a firm does not have to pay out all of its cash flow as dividends, it can instead increase its cash balance, or opposite, it may pay out more than its available to equity holders either by drawing on an existing cash balance or by issuing new securities (bonds or stocks). A dividend discount model will not count for the cash build-up, thus underestimating the value when the firm pays out less than what is available. Opposite, it will overstate the value when the firm is paying out more than what is available. Even though forecasting cash flow to equity holders corrects some drawbacks of the dividend model, it is somewhat cumbersome. Since the cash flows are what is available after the other claimants have taken their share, the model forces you to forecast interest payments, debt repayments, debt issues, etc., which becomes messy and difficult to forecast far out in the future.

To avoid this, it is easier to value the firm's assets and then back out the claims from the debtholders from the value. Rearranging the formula for the firm value, reveals that the value of the equity equals the value of the firm minus the value of the debt. Thus, the items to forecast is the cash flows available to both the shareholders and the debtholders, better known as the free cash flows. The total cash flow available is the cash flows from all the operating activities in the firm, called operating cash flows, subtracted investments which is necessary to maintain the status as a going concern. The formal can be expressed as follows if one assumes no growth in the free cash flows at horizon:

$$Value\ of\ equity_0 = \sum_{t=1}^{t=n} \frac{EBIT(1-t) + depreciation - capex - \Delta working\ capital}{(1+r)^t} + \frac{FCFF_{n+1}/r}{(1+r)^n} - net\ debt_0$$

Operating cash flow equals earnings before interest and tax (EBIT) less tax plus accrual items like depreciation and amortization with no cash effect. It is earnings adjusted for non-cash items. After subtracting capital expenditures and the change in working capital items involved in operations, the free cash flow to the firm's stakeholders is what is left. The formula above is only an approximation since it only accounts for depreciation accruals, but this is a common adjustment (Penman, 2013, p. 123). The free cash flows and the continuing value of the company at the horizon, represented by the value of the perpetuity of the free cash flows at the horizon, are discounted to present and the sum is adjusted for the outstanding net debt in the company. Net debt is debt adjusted for cash, and it is typically reported close to the market value on the balance sheet, so it is generally accepted as an approximation to the true market value (Penman, 2013, p. 116).

#### Advantages and disadvantages

The discounted cash flow valuation model is a concept widely embraced by investors, because it values "hard" cash available to the claimants and it is not blurred by accounting practices. Furthermore, it is more attached to value than the dividend discount model, since it forecasts operating activities which are sources of value creation. However, the model's ignorance of the accrual accounting principles is also the flip side of the coin. It tries to reward the value generating part of the business, but in the short run it punish firms that invest heavily. Since investments do not generate value immediately, capital expenditures destroy value in a discounted cash flow valuation. The investments will create future cash flows, but this is not matched with the value given up. To capture the value of increased investments, the discounted cash flow valuation typically demands a long forecast horizon. Thus, it increases the speculation about the long run, and, as Keynes famously stated, in the long run we are all dead (Penman, 2013, p. 119).

### 5.3.3 THE RESIDUAL INCOME MODEL

The present and near-term future are something we can be fairly confident in when forecasting, but the long run is highly uncertain. To minimize speculation, a valuation technique anchored on what we already know and the close future, should be favoured over a model that recognizes most of the value far out in the infinite future (Penman, 2013, p. 119). The residual income model acknowledges this and values a company based on its current book value on the balance sheet. This model rests on the assumption that no asset is worth more than its book value unless it can generate earnings that are greater than the required return on the asset. Accordingly, the residual income model adjusts the firm's book value up or down dependent on the firm's ability to earn more or less than its required return. The model corrects the missing values on the balance sheet that accountants do not include (Penman, 2013, p. 164). This approach can be used either by anchoring on the current book value of equity and then forecasting comprehensive earnings, or by anchoring on the current invested capital/net operating assets (net debt plus equity) and then forecasting operating income. In any case, the key focus is on residual earnings or residual operating income, which measures the earnings in excess of those required if the book values were to yield at the required rate of return.

#### The residual earnings model

The residual earnings are defined formally as:

$$RE_t = Earnings_t - (required\ return\ on\ equity \cdot Book\ value\ of\ equity_{t-1})$$
$$RE_t = ROE_t \cdot Book\ value_{t-1} - (required\ return\ on\ equity \cdot Book\ value\ of\ equity_{t-1})$$
$$RE_t = (ROE_t - required\ return\ on\ equity) \cdot Book\ value\ of\ equity_{t-1}$$

This formula highlights that return on equity (ROE) and book value drives the residual earnings. The value of the equity if we assume a constant growth rate in residual earnings at the horizon is then:

$$Value\ of\ equity_0 = Book\ value\ of\ equity_0 + \sum_{t=1}^{t=n} \frac{RE_t}{(1+r)^t} + \frac{RE_{n+1}/(r-g)}{(1+r)^n}$$

### The residual operating income model

As in the discounted cash flow model, the value of the equity is the value of the firm less the value of debt. The value of the firm or equivalent the value of the operations can be calculated by adding residual operating income to the current value of the net operating assets (NOA). If we subtract net debt, the value of equity can be stated as:

$$Value\ of\ equity_0 = Net\ operating\ assets_0 + \sum_{t=1}^{t=n} \frac{ReOI_t}{(1+r)^t} + \frac{ReOI_{n+1}/(r-g)}{(1+r)^n} - Value\ of\ net\ debt_0$$

This expression ignores the financing component of the income statement and the balance sheet, increasing the simplicity of the forecast.  The residual operating income (ReOI) can be defined as:

$$ReOI_t = Operating\ income\ after\ tax - required\ return\ on\ net\ operating\ assets$$
$$ReOI_t = ROIC_t \cdot NOA_{t-1} - required\ return\ on\ net\ operating\ assets \cdot NOA_{t-1}$$
$$ReOI_t = (ROIC_t - required\ return\ on\ net\ operating\ assets) \cdot NOA_{t-1}$$

This break-down emphasizes the significance of return on net operating assets (RNOA) and net operating assets on the intrinsic value of equity.

### Advantages and disadvantages

The residual income approach does not punish the company for investments, but rather recognize them as assets. Because of its use of accrual accounting, it matches value added to value given up, and identifies value ahead of cash flows. Coupled with the anchoring on value already recognized in the balance sheet, the characteristics of the model allow the forecasting horizon to be shorter than for discounted cash flow analysis, and it puts less weight on the continuing value of the company. This boils down to a model that is less dependent on speculation. Furthermore, it is also more concentrated around value creation, and increase the awareness of value drivers. On the other hand, the model relies on accounting numbers, which can be manipulated and deceived (Penman, 2013, p. 161). Thus, the model should be used in conjunction with an accounting quality analysis.

### 5.3.4 THE ABNORMAL EARNINGS GROWTH MODEL

The abnormal earnings growth model also put more weight on the immediate future than the distant future, but anchors the valuation on current or forward earnings instead of current book value. With this model, one adds value to capitalised earnings for earnings in excess of normal earnings on prior earnings (Penman, 2013, p. 200). Earnings growth in excess of normal earnings (at the required rate) on prior earnings is the central concept in this method, and this measure is called the abnormal earnings growth. The main principle is that one does not pay for growth that comes from an investment that earns only the required return (Penman, 2013, p. 182). This earnings growth is not based on the reported earnings, but the so called cum-dividend earnings, which is the reported earnings with the dividend reinvested, a concept that recognize that earnings arise from earnings earned by the asset and earnings earned from reinvesting dividends in another asset. Cum-dividend earnings are defined as:

$$Cum\ dividend\ earnings_t = earnings_t + (required\ return \cdot dividend_{t-1})$$

This is compared to earnings that are due to growth at the required return, called normal earnings:

$$Normal\ earnings_t = (1 + required\ return) \cdot earnings_{t-1}$$

The difference between cum-dividend earnings and normal earnings are the abnormal earnings growth:

$$Abnormal\ earnings\ growth_t(AEG) = cum\ dividend\ earnings_t - normal\ earnings_t$$

or expressed as a growth rate relative to the required return rate:

$$AEG_t = (cum\ dividend\ growth\ rate_t - required\ return\ rate) \cdot Earnings_{t-1}$$

If positive, this is growth that adds value, and this is growth we should pay for. The abnormal earnings growth model captures this concept by stating that the value of equity equals capitalised earnings plus extra value for abnormal earnings growth:

$$Value\ of\ equity_0 = \frac{Earnings_1}{r} + \frac{1}{r} \cdot \left[\frac{AEG_2}{(1+r)^1} + \frac{AEG_3}{(1+r)^2} + \cdots + \frac{Continuing\ Value_n}{(1+r)^{n-1}}\right]$$

which is simplified to:

$$Value\ of\ equity_0 = \frac{1}{r} \cdot \left[Earnings_1 + \frac{AEG_2}{(1+r)^1} + \frac{AEG_3}{(1+r)^2} + \cdots + \frac{Continuing\ Value_n}{(1+r)^{n-1}}\right]$$

The formula above anchors the valuation on forward earnings, but it is possible to anchor the valuation on current earnings as well:

$$Value\ of\ equity_0 + d_0 = \frac{(1+r)}{r} \cdot \left[Earnings_0 + \frac{AEG_1}{(1+r)^1} + \frac{AEG_2}{(1+r)^2} + \cdots + \frac{Continuing\ Value_n}{(1+r)^n}\right]$$

This formula assumes that the current earnings grow at the required rate of return and are capitalised along with any future abnormal earnings growth. The value is pre-dividend because current earnings are not reduced by the dividend as with the forward earnings.

#### Advantages and disadvantages

Investors and analysts think in terms of future earnings and earnings growth (Penman, 2013, p. 195). Therefore, the abnormal earnings growth model's narrow focus on earnings aligns nicely with the language of the investor community and the idea that value should be based on what the firm can earn. Furthermore, the model measures value added from selling products by matching revenues with expenses, which is in line with how companies report their numbers. Since the valuation anchors on earnings for the immediate future or current earnings, it demands a shorter forecast horizon and is less reliant on the continuing value. However, the model includes arbitrary factors in every part of the formula, e.g. you are anchoring on current earnings discounted to present at an estimated required rate of return, which increases its sensitivity to subjective inputs, especially compared to the residual earnings model that anchors on the book value.

### 5.3.5 DISCOUNT RATES

The required rate of return is a vital input in the fundamental valuation. This rate represents the amount an investor requires in order to be compensated for time value of money tied up in the investment, and for taking on risk in the investment (Penman, 2013, p. 106). It is also known as the cost of capital or the opportunity cost, because it is the opportunity cost of not taking on an alternative investment with the same risk. It does not exist any exact science on how to estimate the proper required return, but there has been developed some models that tries to quantify the cost of capital, as well as more qualitative approaches that refers to the fundamentals.

#### Asset pricing models

An asset-pricing model gives an estimate of how much an investor should demand in return for investing in an asset. These models, which are widely used, express the cost of equity as the risk-free return plus a risk premium. The risk premium is given by the expected return over the risk-free return on "risk exposures" (factors) that can't be diversified away and the sensitivities of the returns on a specific investment to these factors, known as beta (Penman, 2013, p. 106). If one multiplies the excess return of the risk factor with the beta, it generates the effect of an exposure to a particular risk factor. Summing up all the effects from all risk factors, produces the total risk premium. The capital asset pricing model (CAPM) assumes that you can diversify away a large part of the risk by holding the market portfolio of all investment assets, and, accordingly, the only risk an investor needs to bear and should be rewarded for is the market risk. This is the risk you can't avoid, and a stock's risk premium is defined as its sensitivity to the excess return on the market, calculated as the covariance between the stock return and the market return divided by the variance of the market return. The cost of equity is the required return that should be applied when discounting the forecasted cash flows to shareholders.

The cost of capital for debt is the required return for the firm's debtholders. This is expressed as an after-tax cost of debt, since interest is tax deductible, and generally determined by the riskless rate, the default risk and the tax advantage (Damodaran, 2012, p. 211). The most obvious approach to measure the pre-tax cost of debt is to use its long-term bonds outstanding and compute the yield on the bonds. This works well if the bonds are regularly traded. If not, some companies are also rated by credit agencies, which makes it possible to estimate the cost of debt from the associated default spread. However, many firms do not have credit ratings and outstanding tradeable bonds. To calculate a cost of debt for these firms, it is possible to look at the most recent borrowing history and get a sense of the default spread that has been charged or the analyst can play the role as a credit analyst and assign a rating to the firm based on financial ratios (Damodaran, 2012, pp. 211,212). The latter is accomplished by looking at rated firms and their financial ratios, and compare it to the ratios of the unrated firm. Based on this assessment, the company is given a synthetic rating with an accompanying spread.

Since firms raise money from both equity investors and debt issuers, the cost of capital for the firm is the weighted average of the cost of equity and the cost of debt. The weights are decided by the financing mix, e.g. how much of the firm's value is financed by equity and debt. In principle, the weights should be determined by the intrinsic value of the firm, but since we do not know the value of the equity, market value of the equity is typically used, and it is typically assumed that the book value of debt is close to the market value (Penman, 2013, p. 448). The formula for computing the cost of capital is:

$$Cost\ of\ capital/operations = cost\ of\ equity \cdot \frac{Value\ of\ equity}{Value\ of\ firm} + cost\ of\ debt \cdot \frac{Value\ of\ debt}{Value\ of\ firm}$$

Cost of capital is equivalent to the cost of capital for operations. Thus, the asset pricing models evaluates the riskiness of the firm's operations by only focusing on how the business is financed and not the inherent risk in the operations. On the other hand, operational risk that affects dividends, operating income, earnings or cash flow, should have an impact on the stock price and cause fluctuations. Increased fluctuations should be captured by the sensitivity of the stock price to the market in the CAPM model if the market is efficient. However, if the market misprices the stock and does not price in the increased riskiness of the firm's operations, the beta of the stock will be unchanged. Furthermore, if the operational risk has not increased and the stock market for some irrational reason has sliced the share price relative to the market, the equity risk, according to the CAPM model, has increased. In other words, the market may ignore the fundamentals and cause the cost of capital equation to provide an inadequate risk measure. It is therefore suggested that perception of risk on fundamentals is more appropriate than estimating the risk with betas, based on conceivably inefficient market prices (Penman, 2013, p. 650).

### Fundamental risk factors

Fundamental risk is the risk imposed on the investors as a result of the way a company conduct its activities. Companies handle their activities through financing, investment and operation decisions. Operating risk is the risk from investing and operating activities, while financing risk is the additional risk from financial leverage and borrowing costs. Rearranging the formula for the cost of operations yields:

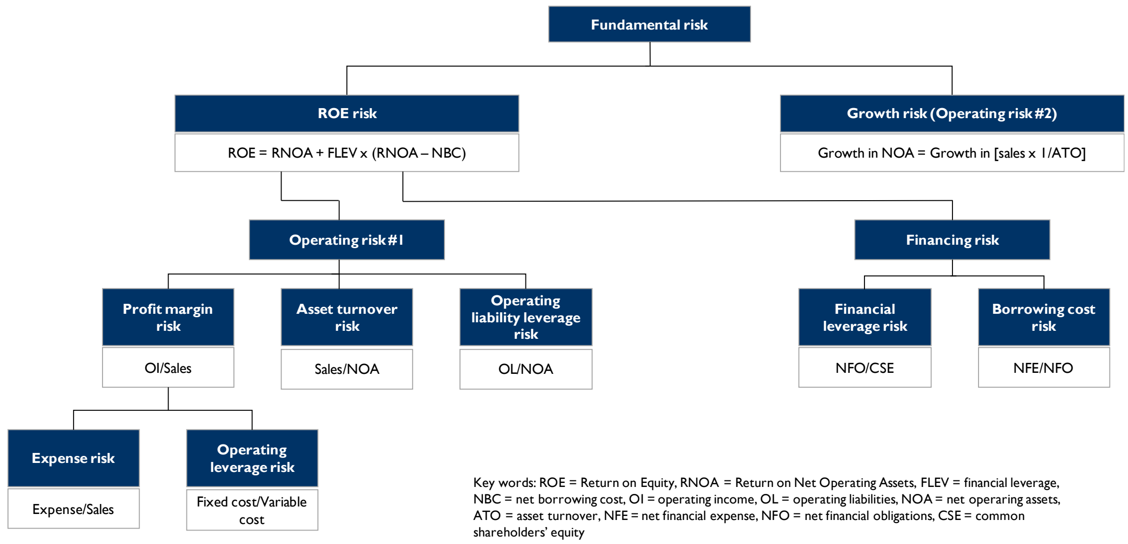
$$Cost\ of\ equity = cost\ of\ operations + \frac{Value\ of\ debt}{Value\ of\ equity} \cdot (cost\ of\ operations - cost\ of\ debt)$$

As clearly seen by the formula, the required return on equity depends on the cost of operations, the operating risk, and the market leverage multiplied by the spread between the required return on operations and the cost of debt, the financing risk. If a firm has no debt, the cost of equity equals the cost of operations, while the cost of equity increases if the leverage rises and the riskier the operations are relative to the cost of debt. Operating risk and financial risk are the basic fundamental determinants of equity risk, and these determinants can be further decomposed into drivers. First, it is important to understand that it is the shareholder value that is at risk. The shareholder value has been estimated in previous sections from fundamentals by applying different models. If we use the residual income model as the starting point, the shareholder value is driven by expectations of future residual earnings, which in turns is driven the return on equity and growth in book value. Thus, the fundamental risk in a company for an equity investor is determined by 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, p. 652).

#### *Operating risk*

Figure 5.3.1 illustrates the drivers of the return on equity and the growth in operating assets. Return on equity is driven by return on net operating assets, financial leverage and the spread between the return on operations and the net borrowing cost. Possible variations in the return on net operating assets, increase the operating risk. Variations in the operating returns can further be explained by variations in profit margins, asset turnovers and operating liability leverage, and these are the key risk factors behind the operational return. The profit margin risk is the risk that the profit margins will change for a given level of sales, and determined by the expense risk and the operating leverage risk.

**Figure 5.3.1 – Fundamental risk factors**




Source: Penman, 2013, p. 652

The expense risk is defined as the risk of expenses such as labour and material costs increase per dollar of sales, while the operating leverage will impact the fluctuations in the profit margins due to the relationship between the company's fixed and variable costs. The asset turnover risk, determined by the velocity of the sales relative to the net operating assets, recognises the possibility of falling sales due to worsening demand or increased competition. If sales are falling, the asset turnover will decrease and reduce the return on net operating assets. Operating liability leverage risk is the risk of a fall in the operating liabilities as a percentage of net operating assets. Operating liabilities reduce the employed net operating assets and lever the return on net operating assets (Penman, 2013, p. 368). Reduced operating liability leverage, implies that the firm is granted less credit from its suppliers, maybe because of less confidence in the firm's ability to pay back in time, which means that its suppliers carry less of the investments in operating assets. This will increase the net operating assets and reduce the return on them.

Return on equity is affected by the financial leverage and the operating spread. A fall in the operating spread creates a downward pressure on the return on equity and this is magnified by the financial leverage. Financial leverage risk is therefore the first component of the firm's financing risk. The leverage is the amount of net financial obligation relative to the common shareholder's equity, and higher financial leverage translates into greater fluctuations in the return on equity when the operating spread is changing. The other part of the financing risk, is the borrowing cost risk. Variations in the borrowing cost will impact the operating spread and the return on equity. If a firm depends heavily on variable-interest-rate debt, it will have a higher borrowing cost risk than a firm with fixed-rate debt.

*Growth risk*

Residual earnings are also driven by growth in net operating assets, where new investments that generate returns greater than the required return increase the value of the firm. Return on equity risk is compounded by the risk that the equity will not increase as anticipated, and as a result, uncertainty about whether the firm can increase investments in net operating assets is an extra aspect of operating risk (Penman, 2013, p. 654). Figure 5.3.1 illustrated this growth risk, and growth in net operating assets is determined by growth in sales, because, for a given asset turnover rate, the amount of net operating asset required is determined by the level of sales (Penman, 2013, p. 654). Growth risk is therefore the risk of the sales not growing as expected. All the aspects of risk covered in this part are summarised in figure 5.3.2.

**Figure 5.3.2 – Summary of risk factors**

<table>
<tr><th colspan="5">Risk</th></tr>
<tr><th colspan="3">Fundamental risk</th><th colspan="2">Asset pricing model risk</th></tr>
<tr><th colspan="2">ROE risk</th><th>Growth risk</th><th>Beta</th><th>Default risk</th></tr>
<tr><td>Operating risk</td><td>Financing risk</td><td>Sales risk</td><td>$\beta = \frac{Cov(Stock\ returns, market\ returns)}{Var(market\ returns)}$</td><td>Credit ratings, yields etc.</td></tr>
</table>

Source: Own creation

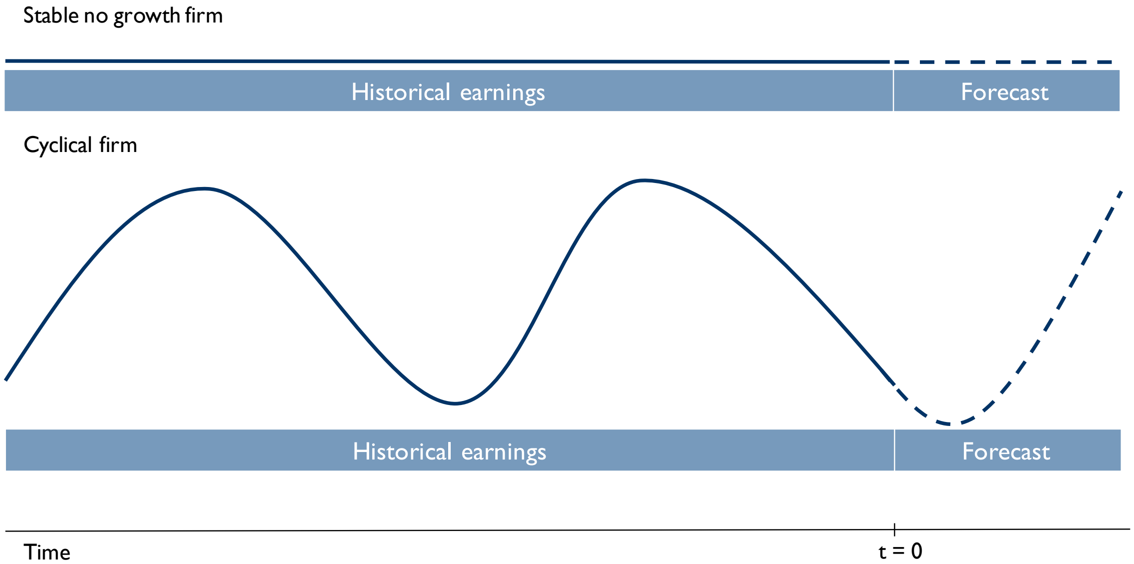
## 5.4 VALUATION OF CYCLICAL COMPANIES

If we ignore all the technicalities, valuation, in its purest form, is all about the future. Both the relative valuation and the fundamental valuation is dependent on assumptions about the future. The fundamental valuation explicitly forecast the future cash flows to the stakeholders, while the relative valuation implicitly assumes something about the future prospects of each firm. This is valid even though the company is cyclical. However, the cyclical nature of the firm complicates the valuation process, and most valuation textbooks write about cyclical companies in separate sections, which underpins the challenges of the value assessment of cyclicals compared to stable companies.

### 5.4.1 EARNINGS THROUGHOUT THE CYCLES

Volatility in earnings is the root to the problems in valuating cyclical companies. Figure 5.4.1 illustrates the difference between a stable firm and a cyclical firm in regard to earnings and forecasts.

**Figure 5.4.1– Earnings and forecast illustration of a stable firm and a cyclical firm**




Source: Own creation

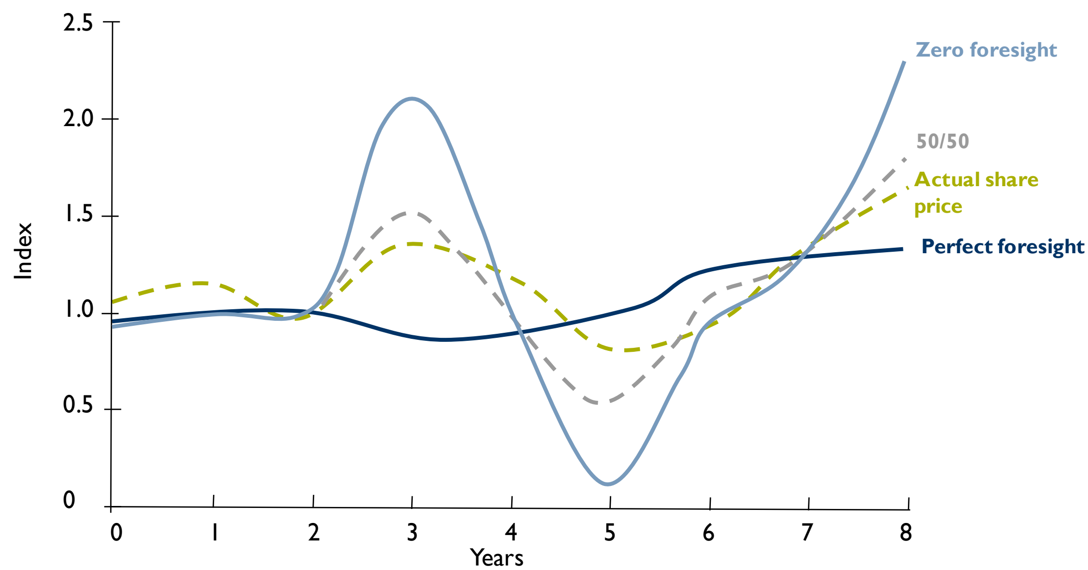
The stable no growth firm has historically had flat earnings. Forecasting future earnings for this firm is simple, it only takes minor motor skills to draw the line into the future. The same would be the case for a stable growing firm. Here, it would be naturally to increase current earnings with the historical growth rate. The cyclical firm is however a completely different story. Due to the cyclicality of the earnings, forecasting the future is much more complicated. The earnings in figure 5.4.1 are currently at the bottom of the cycle, and the historical growth rate the last years has been negative. Extrapolating the negative earnings trend into the future, will be a poor forecast of the future given the cyclicality. Basing the forecast on the current earnings and ignoring the cycle is dangerous, since the cycle is depressing or boosting the earnings, which will give too high values when the cycle is close to the peak and too low values when it is close to the trough. The valuation needs to take into account where the current earnings are in the current cycle. This is extremely difficult, because, as Howard Marks nicely stated, you can only assess the bottom of a cycle in the past tense. Even if it is possible to know where the current cycle is standing, the future cycle must be forecasted as well, and this is often impossible to do (Damodaran, 2012, p. 622). All things considered, the forecast for a cyclical firm is highly uncertain, and the elegantly drawn dashed line in figure 5.4.1 is not a realistic picture of how the market is forecasting the future.

### 5.4.2 MR. MARKETS'S VALUATION OF CYCLICAL STOCKS

Koller, Goedhard, & Wessels (2010) investigates how the market is pricing cyclical stocks. They observed that the share prices were much more volatile than a DCF-valuation with perfect foresight of the industry cycle would predict. This anomaly is explained by investors bias of anchoring on current earnings when predicting the future. Koller, Goedhard and Wessels dive deeper down and examines the equity analysts earnings forecast for 36 cyclical firms over a 12 year period. Their results are facinating. The concensus forecast is completely ignoring the cycle and makes no attempt to predict it. In fact, their forecasts showed an upward trend no matter where the companies were in the cycle. If investors are relying on analysts' forecast of the future, they suggest that concensus' inability or unwillingness to predict the cycle can be a reason for the volatility seen in the share price. In other words, investors relying on concensus' forecasts are implicitly anchoring the future on the current earnings.

Koller, Goedhard and Wessels (2010) do not believe that the market is completely missing the cycles as the concensus of the equity analysts suggests, but they anknowledge that an investor will never have perfect foresight of the market cycle. Instead, they put forward a scenario where an investor uses a blend of perfect foresight and zero foresight. Figure 5.4.2 is a reproduction of Koller, Goedhard and Wessels graph where they value four-year cyclical companies with three different levels of foresight. The perfect foresight scenario is the scenario where investors have perfect foresight about the industry cycle. As seen by the line, the valuation with perfect foresight is very stable, because no single year's earnings has a significant impact on the value of the company (Koller, Goedhard, & Wessels, 2010, p. 756), compared to the actual share price. The zero foresight scenario is the scenario where investors are anchoring on current performance and assuming that this represents a data point on a new long-term trend (Koller, Goedhard, & Wessels, 2010, p. 759). This scenario shows massive fluctutations in the value estimate, highlighting that investors will assign too much value close to the peak and too little at the bottom. The grey line illustrates the scenario where the investor weights the perfect foresight scenario and the zero foresight scenario with 50% each. Evidently seen by the graph, this line is much closer to the actual share price than the two other scenarios. This simple illustration suggests that the market neither has perfect foresight nor zero foresight. The results imply that Mr. Market tries to forecast the cycle based on past cycles, but also assigns some probability to a scenario where the company breaks out of the old cycle based on the current performance.

**Figure 5.4.2 – Market Values of Cyclical Companies: Forecast with Three Levels of Foresight**

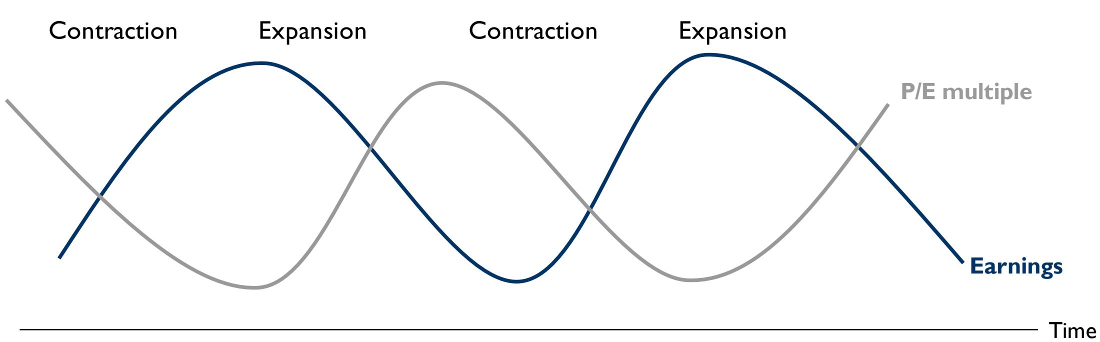



Source: Koller, Goedhard, & Wessels, 2010, p. 760

### 5.4.3 MULTIPLES AND CYCLICAL COMPANIES

The multiples of cyclical companies will behave differently than multiples of stable companies. More specifically, the multiples will exhibit much more volatility than a stable firm and change as we move through the cycle. The price to earnings multiple, for instance, will likely 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, investors presumably have an expectation about a down-turn just around the corner, consequently assigning a lower multiple because of poor growth outlooks at the top. Opposite, the multiple will be most expensive at the bottom, because of expectations for a coming upturn and corresponding higher growth.

**Figure 5.4.3 - Expected P/E multiple contraction and expansion in cyclical stocks**



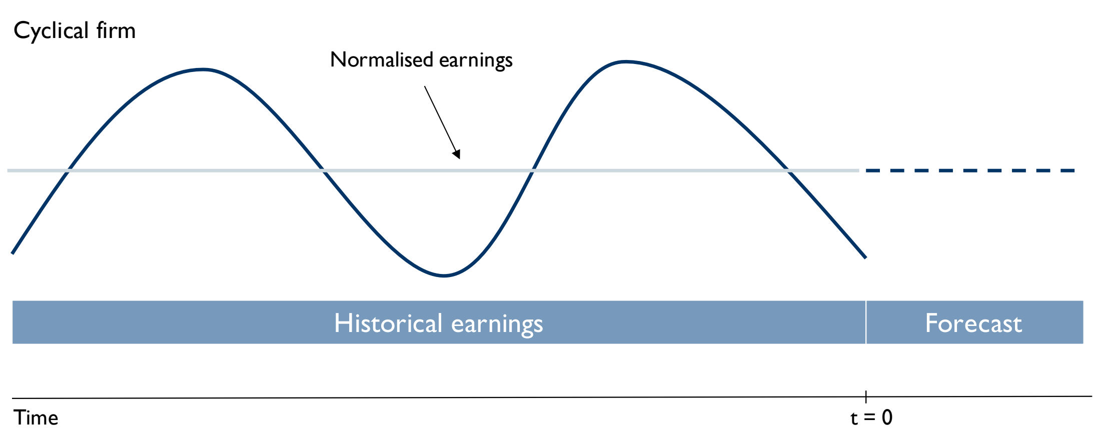

Source: Own creation

Figure 5.4.3 illustrates a thought pattern of the P/E multiple for a cyclical company. This evolvement assumes that the earnings are falling more and faster than the share price, resulting in peaks and valleys inversely related to the earnings cycle. If investors have perfect foresight and see "through" the cycle, this will be the case. However, investors are also focused on current earnings (base year fixation), evidently seen by the volatility in the share price in figure 5.5. This implies that investors 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 most likely will have a dampening effect on the illustrated contraction and expansion pattern in figure 5.6.

### 5.4.2 REMEDIES FOR CYCLICAL EARNINGS

Benjamin Graham, the father of value investing and the "Dean of Wall Street", came up with a solution to the difficulties of valuing cyclical companies over 70 years ago. He suggested that investors should pay for the average earnings of the past decade, a time-frame supposed to cover a complete cycle – evening out the highs and lows (Graham, The Intelligent Investor, 1973, p. 168). This approach is called "normalising" and is one of few methods suggested by literature on valuation of cyclical stocks. Normalising involves ignoring the cycle forecast and instead focus on understanding what the company will earn in a normal year. A normal year is defined as a year where earnings are neither depressed nor pushed up by the cycle, i.e. a year that reflects the mid-point of the cycle or where commodity prices reflect the underlying equilibrium between demand and supply (Damodaran, 2009). Using the normal year as the base year for forecasts, will lead to a more conservative forecast of revenues in a peak year or a higher forecast in the trough of the cycle.

**Figure 5.4.4 - Normal year for a cyclical company**



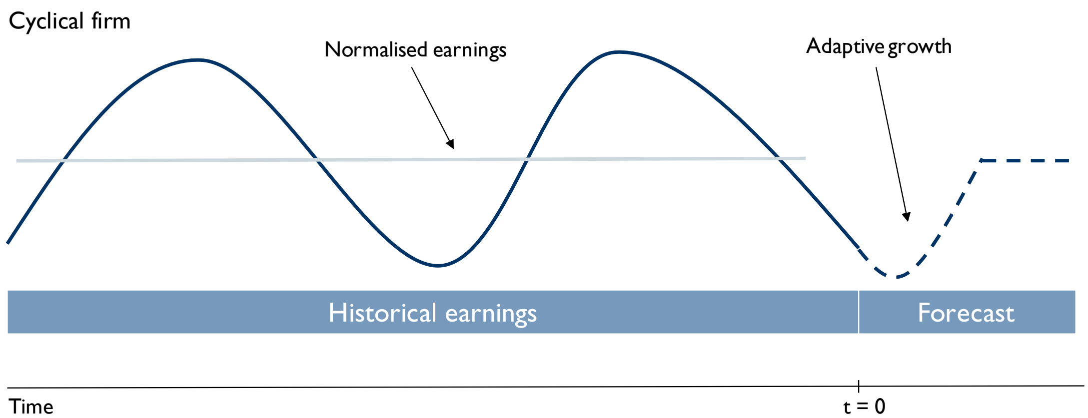

Source: Own creation

Figure 5.4.4 illustrates the concept of normalising. The earnings are averaged to find the mid-cycle earnings level and this is used as the starting point for forecasting the future. This approach is most suitable for cyclical firms in mature businesses, since it assumes that earnings quickly will revert back to normal levels

(Damodaran, 2012, p. 619), which may not be case for a cyclical firm that has increased its asset base severely. Moreover, when current earnings are replaced with normalised earnings, the implicit assumption is that the normalisation will occur immediately.

This is a harsh assumption, since it can take a long time before a cycle correct itself, and this may cause distorted valuations in the meantime. A way out of this trouble is to allow earnings to follow the current cycle for the short term, and normalize in the long term (Damodaran, 2009). For instance, at the apparent bottom of the cycle, the growth rates are adjusted upwards to reflect the expected recovery and haul us back to normality. Figure 5.4.5 below demonstrates this concept. The method requires a forecast of the cycle in the short term, and is therefore a compromise between normalising and forecasting the cycle.

**Figure 5.4.5 - Adaptive growth and normalisation in the long term**




Source: Own creation

If the normalised environment reflect what the firm can earn in a normal year, there must be some consistency in how the market values corporations relative to these earnings (Damodaran, 2009). Benjamin Graham actually referred to the P/E ratio when he talked about averaging a decade of earnings, and using average earnings in the denominator transforms the multiple to a normalised P/E multiple. By normalising the multiple, the valuation is looking past the cycle and Damodaran (2009) states that in the absence of differences in growth and risk among the companies, all should trade at the same multiple of normalised earnings. Thus, if the cycle affects each firm equally, the only reason for divergent standardised prices is that some firms have brighter growth prospects or are less risky than others.

Normalised multiples will be more stable than multiples based on trailing or current earnings, but using unadjusted multiples may also serve a purpose in valuation serve the purpose of the valuation anyway, such as if the earnings for all companies in the cyclical sector move in lock-step (Damodaran, 2009).

# THEORETICAL MULTIPLE DRIVERS

The valuation theory in the previous section described two methods for valuing companies, the relative and the fundamental approach. It was argued that a relative valuation should take into account differences among companies to justify why a company should trade in line with the sector or why it deserved a different valuation, while the fundamental approach arrived at a fair value by discounting the future value creation from the firm to present. The fundamental approach explicitly states the assumptions about key characteristics and future prospects of the company, whereas the relative approach implicitly makes assumption about the same things. This section will provide a bridge between the relative valuation and the fundamental valuation in order to reveal fundamental drivers of the multiples, which enable us to form initial hypotheses on how fundamental variables affect the multiples.

## 6.1 MULTIPLE SELECTION

The usual discussion on what multiple to use when doing a relative valuation often concerns the shortcomings of each multiple. This makes sense since the regular relative valuation often naively choose a multiple and apply it on the relevant company, ignoring the implicit assumptions of each multiple, and thus, treat all peers alike. The shortcomings, or implicit assumptions, of the multiples are not revealed until the multiples are seen through the lens of a fundamentalist, i.e. by anchoring the multiples on a fundamental valuation technique. Because of the different assumptions behind each multiple, there has been developed some preferences over time when it comes to multiples best suited for different industries, mainly to reduce time spent on controlling for differences.

Five groups of multiples stand out: accrual flow multiples, book value multiples, cash flow multiples, forward-looking multiples and alternative multiples (Schreiner, 2007, p. 39). 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, the cash flow multiples make use of cash flow metrics in the denominator, while alternative multiples adjust the other multiples for items like research and development costs, amortization of intangible assets etc. The forward-looking multiples use a forecast of the value driver when calculating the multiple.

There are as many multiples as there are accounting numbers, but due to space limitations this thesis will only focus on four commonly applied multiples we believe that investors may use in their investment process, more specifically, price to book value, enterprise value to EBITDA-, enterprise value to sales and price to earnings.

### 6.1.1 THE PRICE TO BOOK VALUE MULTIPLE

The price to book value of equity multiple, hereinafter called the P/B multiple, is best used for capital intensive firms where the tangible assets are the source of value (Frykman & Tolleryd, 2003, p. 65). Both the shipping industry and the oil industry are sectors that demand heavy investments and where tangible assets like ships and oil fields are key for future earnings power and value creation. Furthermore, Schreiner (2007) finds that P/B is the most accurate multiple in the oil industry when he investigates the accuracy of different multiples on different industries. The P/B multiple also has an intuitively appeal, since book value equals net assets and you are buying the company's assets. A more practical reason for using the P/B multiple is that companies seldom have negative book values, which will increase the sample size when evaluating the multiple.

### 6.1.2 THE ENTERPRISE VALUE TO EBITDA MULTIPLE

The enterprise value to EBITDA multiple, hereinafter called the EV/EBITDA multiple, is a darling in the investment society and probably one of the most popular EV multiples (UBS Warburg, 2001, p. 29). This may be because of its pre-depreciation characteristic, which makes it closer to cash flow, and cash flow is something investors care about. Moreover, it eliminates the arbitrariness in relation to depreciation and tax regimes, and it is less affected by differences in capital structure, since it measures the unlevered value of the company. However, it is still affected by differences in capital intensity (measured as depreciation as a percentage of EBITDA), which means that the EV/EBITDA multiple is quite suitable for the oil and dry bulk industry because of greater homogeneity among firms, than for example the retail industry. (UBS Warburg, 2001, p. 30). Since EBITDA is an accounting number close to the top of the income statement and before any non-cash expenses, most businesses are positive on EBITDA, thus, the multiple are still able to produce a standardised price even when the earnings are negative, widening the universe of companies, and strengthening the robustness of the multiple.

### 6.1.3 THE ENTERPRISE VALUE TO SALES MULTIPLE

The enterprise value to sales multiple, hereinafter called the EV/Sales multiple, is based on the very top of the income statement. It is the enterprise value compared to the revenue, and unlike items further down the income statement, sales will never turn negative even in the worst down cycle. In industries where the earnings are volatile and fail to represent the long term potential, it is recommended to use the EV/Sales multiple (Koller, Goedhard, & Wessels, 2010, p. 327). Both the shipping and oil industry witness highly volatile earnings, making the EV/Sales very applicable, and since the sale measure never turns negative, the sample will also be close to complete.

### 6.1.4 THE PRICE TO EARNINGS MULTIPLE

The price to earnings multiple, hereinafter called the P/E multiple, is part of any multiples valuation in practice, and it gained serious popularity in the early 1930s (Schreiner, 2007, p. 41). This multiple prices companies on the very bottom line of the income statement, the earnings, which makes intuitive sense - a company should often be worth more if it is able to grow its earnings. The P/E multiple is affected by different accounting practises, capital structure and it is claimed that it does not have any meaning if a firm has a low net income (Pereiro, 2002, p. 253). Schreiner (2007) argues that the P/E multiple, from a theoretical point of view, should be applied in industries with solid earnings, with uniform accounting practises and similar capital structure. This is rarely fulfilled, but since investors still care about the bottom line and everyone uses it, we will include it in the analysis, even though there will be fewer firms available because of negative earnings.

## 6.2 PRICE TO BOOK VALUE

The residual income model anchors on book values and the price over the book value is determined by the residual income from the firm. Thus, this model is suitable in order to uncover the drivers of the price-to-book multiple, which express the relationship between the market's perception of the "real" book value and the actual accounting value. If we apply the residual income model for a stable growth environment, it is possible to get a simple overview of the fundamental determinants of the P/B multiple:

$$P_0 = B_0 + \frac{RE_1}{r_e - g^{RE}}$$

Exploiting the fact that residual earnings is determined by the difference between the return on equity and the cost of equity multiplied by the book value, gives the following expression:

$$P_0 = B_0 + \frac{(ROE_1 - r_e) * B_0}{r_e - g^{RE}}$$

The growth rate in the residual earnings, assuming a constant return on equity, is:

$$Growth\ in\ RE = \frac{(ROE_1 - r_e) * B_0}{(ROE_0 - r_e) * B_{-1}} = B_0/B_{-1}$$

Thus, we can substitute the growth in residual earnings with the growth in book value of equity, since growth comes from growth in the book value of equity and not increase in the return on equity.

Dividing both sides by the book value of equity, grants the formula for the P/B multiple:

$$\frac{P_0}{B_0} = 1 + \frac{(ROE_1 - r_e)}{r_e - g^{Book\ value}}$$

The formula above reveals that the P/B multiple is calculated as the normal P/B multiple (this equals 1) plus the difference between the return on equity and cost of equity growing at a constant rate $g$ discounted to present. Thus, if a firm does not create any residual earnings, the firm should trade at the normal P/B multiple of 1 - it is not worth more than the value recognised om the balance sheet. To justify a valuation above its book value, it is therefore crucial that the firm generates a value over the cost of equity going forward. According to the fundamental formula for the P/B multiple, return on equity, growth in book value and cost of equity are the drivers behind the multiple. All else equal, a firm with high return on equity, low risk and high growth should trade at a higher P/B multiple than a firm with the opposite characteristics.

## 6.3 PRICE TO EARNINGS

### 6.3.1 P/E DERIVED FROM THE ABNORMAL EARNINGS GROWTH MODEL

The abnormal earnings growth determined the intrinsic price of the company by anchoring on forward earnings or current earnings and applied extra value over this only if the cum-dividend growth in earnings was higher than the required return. If we assume a stable growth phase, the forward price-to-earnings multiple can be derived in this manner:

$$P_0 = \frac{1}{r_e} \cdot \left[ E_1 + \frac{g_{1-2}^{cum\ div\ earnings} - r_e}{r_e - g^{AEG=RE=Book\ value}} \right]$$

Dividing by the forward earnings on each side gives the forward P/E multiple:

$$\frac{P_0}{E_1} = \frac{1}{r_e} \cdot \left[ 1 + \frac{g_{1-2}^{cum\ div\ earnings} - r_e}{r_e - g^{AEG=RE=book\ value}} \right]$$

This formula shows that if a firm do not create abnormal earnings growth, the forward P/E equals $1/r_e$, the normal forward P/E multiple. A company should trade at premium to its normal P/E ratio only if it is able to generate abnormal earnings growth. The trailing P/E multiple can be derived in a similar way:

$$P_0 = \frac{(1+r)}{r} \cdot \left[ Earnings_0 + \frac{g_{0-1}^{cum\ div\ earnings} - r_e}{r_e - g^{AEG=RE=book\ value}} \right]$$

Dividing both sides with current trailing earnings yields the trailing P/E multiple:

$$\frac{P_0}{E_0} = \frac{(1+r)}{r} \cdot \left[ 1 + \frac{g_{0-1}^{cum\ div\ earnings} - r_e}{r_e - g^{AEG=RE=Book\ Value}} \right]$$

Thus, the trailing P/E ratio equals the normal trailing P/E multiple, $(1 + r)/r$, plus a premium for abnormal earnings growth. This derivation proves theoretically that growth in cum-dividend earnings one period ahead, abnormal earnings growth and risk, are the key determinants of the P/E multiple.

### 6.3.2 P/E DERIVED FROM THE DIVIDEND DISCOUNT MODEL

It is also possible to determine the fundamental P/E multiple from the dividend discount model for a stable growth environment:

$$P_0 = \frac{Dividend_1}{r - g^{earnings}}$$

Rewriting the dividend as a function of earnings and the pay-out ratio:

$$P_0 = \frac{Earnings_1 \cdot Pay\ out\ ratio}{r - g^{earnings}}$$

Recognizing that the pay-out ratio equals 1 minus the retention ratio:

$$P_0 = \frac{Earnings_1 \cdot (1 - retention\ ratio)}{r - g^{earnings}}$$

Retention ratio is a function of growth and return on equity:

$$P_0 = \frac{Earnings_1 \cdot (1 - \frac{g^{earnings}}{ROE})}{r - g^{earnings}}$$

Dividing both sides with forward earnings gives the P/E ratio:

$$\frac{P_0}{E_1} = \frac{1 - g^{earnings}/_{ROE}}{r - g^{earnings}}$$

And the trailing P/E ratio can be expressed as:

$$\frac{P_0}{E_0} = \frac{1 - g^{earnings}/_{ROE}}{r - g^{earnings}} \cdot (1 + g^{earnings})$$

Using the dividend discount model to derive the P/E multiple reveals that the return on equity is a fundamental driver of the P/E multiple as well.

## 6.4 ENTERPRISE VALUE TO EBITDA

The discounted cash flow valuation focuses on the investing and operating activities of the firm, and it computes the value of the firm by forecasting future free cash flows. The value of the firm is equivalent to the value of the operations and is also called the enterprise value. Thus, it is appropriate to use the discounted free cash flow to firm valuation in order to derive the enterprise value-to-EBITDA multiple (EV/EBITDA). Assuming stable growth and constant factors across time:

$$EV_0 = \frac{FCFF_1}{cost\ of\ operations - g^{FCFF}} = \frac{EBIT_1(1-t) + depreciation - capex - \Delta working\ capital}{cost\ of\ operations - g^{FCFF}}$$

$$= \frac{EBIT_1 * (1-t) - (capex - depreciation + \Delta working\ capital)}{cost\ of\ operations - g^{FCFF}} = \frac{EBIT_1(1-t) - Reinvestment_1}{cost\ of\ operations - g^{FCFF}}$$

Expressing reinvestments as a percentage of $EBIT(1-t)$, the reinvestment rate:

$$EV_0 = \frac{EBIT_1(1-t) * (1 - reinvestment\ rate_1)}{cost\ of\ operations - g^{FCFF}}$$

The growth rate in FCFF can be written as:

$$g^{FCFF} = \frac{EBIT_1(1-t)*(1-reinvestment\ rate_1)}{EBIT_0(1-t)*(1-reinvestment\ rate_0)}$$

If we assume that the reinvestment rate is constant, the growth in FCFF equals the growth rate in the operating income. Dividing both sides by EBIT, yields the forward EV/EBIT multiple:

$$\frac{EV_0}{EBIT_1} = \frac{(1-t)\cdot(1-Reinvestment\ rate_1)}{cost\ of\ operations - g^{operating\ income}}$$

The reinvestment rate can be expressed as a function of ROIC and growth since we assume constant growth on $EBIT(1-t)$ and a constant reinvestment rate:

$$\frac{EV_0}{EBIT_1} = \frac{(1-t)\cdot(1-\frac{g^{operating\ income}}{ROIC})}{cost\ of\ operations - g^{operating\ income}}$$

If we express EBIT as $EBITDA(1-D)$, where $D$ is depreciation as a percentage of EBITDA, and divide both denominators with $(1-D)$ and $(1+g)$, we get the current EV/EBITDA multiple:

$$\frac{EV_0}{EBITDA_0} = \frac{(1-t)*\left[1-\frac{g^{operating\ income}}{ROIC}\right]*(1-D)}{cost\ of\ operations - g^{operating\ income}} * (1+g^{operating\ income})$$

This derivation points at profitability, measured with ROIC, and growth as positive drivers of the multiple, while the capital intensity, expressed as the depreciation percentage of EBITDA, risk and tax are negative contributors.

## 6.5 ENTERPRISE VALUE TO SALES

Similarly, the enterprise value-to-sales (EV/Sales) multiple can be derived from the discounted free cash flow model. Dividing both sides with sales and both denominators with $(1+g)$, produce the current EV/Sales multiple:

$$\frac{EV_0}{Sales_0} = \frac{\frac{EBIT_1}{Sales_1}\cdot(1-Reinvestment\ rate_1)\cdot(1-t)}{cost\ of\ operations - g^{operating\ income}}\cdot\left(1+g^{operating\ income}\right)$$

Recognising that $EBIT_1/Sales_1$ is the EBIT-margin, yields:

$$\frac{EV_0}{Sales_0} = \frac{EBIT\ margin\cdot(1-Reinvestment\ rate)\cdot(1-t)}{cost\ of\ operations - g^{operating\ income}}\cdot(1+g^{operating\ income})$$

The numerator in the above multiple expression is equivalent to the FCFF as a percentage of sales (FCFF-margin), thus the multiple can also be written as:

$$\frac{EV_0}{Sales_0} = \frac{FCFF\ margin}{cost\ of\ operations - g^{operating\ income}}\cdot(1+g^{operating\ income})$$

The formulas for the intrinsic EV/Sales multiples demonstrate that EBIT-margins, FCFF-margins, tax, growth and risk play key roles for the multiple.

## 6.6 SUMMARY TABLES & HYPOTHESES

The tables below summaries the above derivation of the intrinsic multiples and highlight the key drivers of each multiple.

**Figure 6.6.1 - Summary table of intrinsic P/B and P/E multiples and key drivers**

| | P/B | P/E | P/E |
|---|---|---|---|
| **Valuation model** | Residual income model | Abnormal earnings growth model | Dividend discount model |
| **Simple model** | $P_0 = B_0 + \frac{RE_1}{r_e - g^{RE}}$ | $P_0 = \frac{(1+r)}{r} * \left[Earnings_0 + \frac{g_{0-1}^{cum\ div\ earnings} - r_e}{r_e - g^{AEG=RE=book\ value}}\right]$ | $P_0 = \frac{Dividend_1}{r - g^{earnings}}$ |
| **Intrinsic multiple** | $\frac{P_0}{B_0} = 1 + \frac{(ROE_1 - r_e)}{r_e - g^{book\ value}}$ | $\frac{P_0}{E_0} = \frac{(1+r)}{r} * \left[1 + \frac{g_{0-1}^{cum\ div\ earnings} - r_e}{r_e - g^{AEG=RE=Book\ Value}}\right]$ | $\frac{P_0}{E_0} = \frac{1 - g^{earnings}/ROE}{r - g^{earnings}} * (1 + g^{earnings})$ |
| **Key drivers** | ROE, growth, cost of equity | Cost of equity, cum-dividend growth rate, growth in AEG | ROE, growth, cost of equity |

Source: Own Creation

**Figure 6.6.2 - Summary table of intrinsic EV/EBITDA and EV/Sales multiples and key drivers**

| | EV/EBITDA | EV/Sales |
|---|---|---|
| **Valuation model** | Discounted free cash flow model | Discounted free cash flow model |
| **Simple model** | $EV_0 = \frac{FCFF_1}{cost\ of\ operations\ - g^{FCFF}}$ | $EV_0 = \frac{FCFF_1}{cost\ of\ operations\ - g^{FCFF}}$ |
| **Intrinsic multiple** | $\frac{EV_0}{EBITDA_0} = \frac{(1-t) * \left[1 - \frac{g^{operating\ income}}{ROIC}\right] * (1-D)}{cost\ of\ operations - g^{operating\ income}} * (1 + g^{operating\ income})$ | $\frac{EV_0}{Sales_0} = \frac{EBIT\ margin * (1 - Reinvestment\ rate) * (1-t)}{cost\ of\ operations - g^{operating\ income}} * (1 + g^{operating\ income})$ |
| **Key drivers** | Capital intensity, ROIC, reinvestment rate, growth, cost of operations, tax | EBIT-margin, reinvestment rate, ROIC, growth, cost of operations, tax |

Source: Own creation

Doing a relative valuation without thinking about the key drivers, is like working at the immigration office and evaluating each hopeful without looking at their passports. A simple relative valuation solves the issue of company dissimilarities by simply assuming that each company in the peer group/sector is identical regarding profitability, growth and risk. This is however not a clever way of solving the problem, and if you want to value a company on a relative basis, it is, at least on a theoretical basis, crucial to control for differences in the key drivers.

The theoretic links between multiples and fundamental drivers, in combination with the review of the cost of equity and cost of capital in section 5.3.5, inspired the initial hypothesis on how fundamentals affect investors valuation of the companies in the E&P and dry bulk sector.

**Hypothesis 1.1**

*There is a significant (…) relationship between the Y(n) and the X(n) in figure 6.6.3.*

**Figure 6.6.3 - Hypothesis 1.1**

| | | Independent variable X (n) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
| n | | ROE | ROIC | EBIT-margin | NOPAT-margin | Growth | Capital intensity | Reinvestment rate | Beta | Profit margin risk | Op.liability risk | Debt to equity |
| Dependent variable Y (n) 1 | P/B | pos. | | | | pos. | | | neg. | neg. | neg. | neg. |
| 2 | P/E | pos. | | | | pos. | | | neg. | neg. | neg. | neg. |
| 3 | EV/EBITDA | | pos. | | | pos. | neg. | neg. | neg. | neg. | neg. | |
| 4 | EV/Sales | | pos. | pos. | pos. | pos. | | neg. | neg. | neg. | neg. | |

Source: Own creation

# DATA & CONSTRUCTION OF A DATA BASE

This thesis operates in the purgatory between valuation theories and the markets' actual observable behaviour across time. To express any plausible opinions or draw any conclusions without being accused of complete guesswork, data is the single most important input. Data provides us with crucial information that can be interpreted, understood and empowered by the context it is observed in. However, the quality of conclusions or results can never be any better than the quality of the input. In other words, if the analysis relies on garbage, the results will also be garbage. Given the abundance of data in today's world and our reliance on data, this section will give an overview of how the data is collected and processed in this thesis.

## 7.1 SCREENING STRATEGY

First, this thesis anchors on accounting data and price data, which naturally narrows the universe of companies to public listed companies. Accordingly, the initial sample of companies was selected using Bloomberg's equity screener function. This function allows you to screen for companies based on several different criteria. The cross-sectional approach tolerates companies leaving and entering the sample at different points in time, because the analysis at each point in time is only conducted based on the available sample of companies, i.e. companies with a complete data set, at that point in time. It is however something that should be noted when we perform pooled cross-sectional analysis. Nevertheless, companies that are delisted, suspended, acquired, etc. were all included in the first stage of the screening process, which reduce the survivorship bias.

In the second stage, companies in the relevant sectors were chosen. Bloomberg gives the user the option to screen on many different industries in a drop-down menu based on different industry classification systems. The default industry classification setting is the ICB-system, and this was therefore used to single out the relevant sectors. The "Exploration & Production" and the "Integrated Oil & Gas" sectors were selected to represent the entire universe of oil companies focused on the upstream and downstream part of the oil industry, while the "Marine Transportation" narrowed the transportation sector down to seaborne trade shipping. Further refinement was made on the shipping sector by only including those companies with a company description including the phrase "dry bulk".

Lastly, only companies that have ISIN-numbers were included and the oil universe was restricted to only include companies with a positive market capitalization. This final screener resulted in tickers and ISIN-numbers for over a thousand oil companies and over sixty dry bulk companies. See appendix 7.1 for screenshots of the screening strategy.

Since the thesis' focus shifted from the broad definition of the oil industry to only concentrate on the upstream segment, and integrated oil companies collect parts of their revenue from the downstream segment of the industry, all integrated oil companies were removed from the sample, leaving 949 E&P companies in the initial sample.

The tickers and ISIN-numbers of the companies in the sectors were then fed into COMPUSTAT, a database that contains accounting numbers on a large global sample of companies, to get accounting information on each company. Some of the companies in the sample did not exist in the database, which further reduced to a final sample of 657 E&P companies and 47 dry bulk companies as displayed in appendix 7.2.

The final samples are varied and consist of both small, medium and large companies, and the screening strategy is executed with as few assumptions as possible. This decreases bias in the sample and increases the credibility of our analysis. Moreover, it increases the relevance of our results, since we are not restricting ourselves to only looking at companies considered to be large in terms of market capitalisation.

## 7.2 DATA EXTRACTION

Eighteen historical accounting numbers from both the income statement and the balance sheet were collected for each company in both samples from COMPUSTAT. The multiple analysis in section 6 uncovered several drivers of the different multiples, and these drivers were decisive for the chosen accounting numbers. Appendix 7.3 gives a complete overview of the accounting numbers that were extracted, ranging from current assets to depreciation and amortization.

Since the thesis is trying to get an understanding of what investors consider to be important when appraising a company with highly cyclical/volatile earnings and ultimately wants to create a model to price cyclical companies, we desired historical data spanning over at least one cycle. COMPUSTAT has accounting numbers dating back to 1969 for US companies and 1988 for non-US companies, which obviously limited our period to these years, but gave us enough history to cover multiple cyclical periods. Accounting data for each quarter from 1969 to the third quarter of 2016 were collected for the E&P sector, while we extracted quarterly data from the first quarter of 1988 for the dry bulk sector.

In total, approximately 356,000 accounting numbers were pulled out for the E&P sector, ~26,000 numbers per variable, and roughly 17,000 quarterly numbers were collected for the dry bulk sector, ~1,500 numbers per variable. COMPUSTAT is responsible for the quality of the accounting data for each company in their database, so we cannot guarantee that their collection process is free for errors. With this in mind, we have done numerous sample tests to check the quality of the data, and most of the tests confirmed the validity of the data.

Share price data for each company in the samples were collected from Bloomberg. More specifically, we used the Bloomberg Excel Add-in because it lets you extract a large number of data with just a few keystrokes. Quarterly stock price data for the entire period from 1969 to today were collected, and Appendix 7.4 gives an example of how we built the excel formula. The stock prices we collected are not dividend adjusted, and although this should not be a huge problem, it could have a downward impact on some of the calculated trailing multiples for companies that pay out dividends.

The Bloomberg Excel Add-in was also used to get data on company betas. We used the formula seen in Appendix 7.5 to extract quarterly betas on each company over the entire period. The formula calculates the raw beta for a company each quarter based on weekly stock prices the last three years regressed against the firm's local market index. The standard period used by providers of beta estimates is between two years and five years (Damodaran, Investment Valuation - Tools and Techniques for Determining the Value of Any Asset, 2012, p. 188), where a longer estimation period offers more stable data, but may be misleading due to changes in the firm's risk characteristics over the period. Three years were therefore chosen as something in between. Weekly intervals are the default setting in the Bloomberg beta estimation, but this is also recommended because it reduces the non-trading bias significantly (Damodaran, Investment Valuation - Tools and Techniques for Determining the Value of Any Asset, 2012, p. 188), and was therefore kept in the formula. There are however some weaknesses with the beta estimate provided by Bloomberg. Firstly, Bloomberg ignores dividends, which has an impact on stocks that either pay no dividends or have a higher pay-out ratio than the market. Lastly, since we have chosen to keep the default setting of regressing against the local market index, the estimate may not be appropriate for an international or cross-border investor. All things considered. the beta estimates contain some weaknesses, but are still considered appropriate given the scope and purpose of their function in the analysis.

## 7.3 DATA PREPARATION

The above-mentioned data are the foundation of the analysis. However, they still have to be restructured into a usable format suitable for the quarterly and pooled cross-sectional regression analysis, and the descriptive quantitative industry analysis.

### 7.3.1 MULTIPLES

There are at least two applicable strategies when exploring the relationship between market values and fundamentals: The analysis can be performed on an absolute basis, using absolute market values, or it can be done on a scaled basis, where the market values are scaled against a common variable. The work of Abrams (2012) finds that the use of a scaled dependent variable minimizes or reduces the statistical issue of heteroscedasticity, but that the adjusted $R^2$ tend to be lower. Consequently, this thesis applies scaled variables, i.e. multiples, as the dependent variables instead of the absolute market value in order to reduce heteroscedasticity, but we recognise that this may yield lower adjusted $R^2$ values.

The numerator in the multiple is always the most recent available number of the market price or the enterprise value, while there is much less consistency in the denominator. In practice, the denominator can either refer to the current value driver, the trailing value driver or the forward value driver. This thesis applied the so called trailing 12-month multiple, which means that we use the trailing 12-month value driver in the denominator, due to the nature of our data and limited access to analysts' estimates of future value drivers.

To secure uniformity and valid comparison, the multiples were calculated by using raw accounting data from COMPUSTAT and price data from Bloomberg, instead of directly obtaining them multiples from Bloomberg or another external resource. The numerator in the equity multiples is the registered stock price at the close of each quarter, while the enterprise multiples' numerator is the stock price plus the net interest bearing debt at each quarter, which is long term debt less cash. The denominator in the P/E, EV/sales and EV/EBITDA multiple in this thesis is the last four quarters of the value driver accumulated, while the denominator in the price-to-book multiple is the reported book value of equity in the relevant period (this number is a balance sheet item, so no adjustment is needed).

If a company in the sample does not have four consecutive quarters of data on the value driver, then the multiple that quarter is dismissed. It should also be noted that we have lagged the denominator one quarter compared to the numerator in the multiple, since investors do not have access to accounting numbers for the same quarter the price is observed in. Thus, the trailing multiples used for each quarter, exemplified by the P/E multiple and the P/B multiple, in this thesis are defined as:

$$1)\ \frac{Price}{Trailing\ earnings} = \frac{Market\ value_t}{(Earnings_{t-1} + Earnings_{t-2} + Earnings_{t-3} + Earnings_{t-4})} = \frac{Market\ value_t}{Trailing\ earnings_{t-1}}$$

$$2)\ \frac{Price}{Book\ value\ of\ equity} = \frac{Market\ value_t}{Book\ Value\ of\ equity_{t-1}}$$

Price data extracted from Bloomberg were limited to the third quarter of 1980. Thus, the trailing multiples in the E&P sector were calculated from the third quarter of 1980, while they were calculated from the first quarter of 1999 for the universe of dry bulk companies (although our dry bulk sample does not reach a meaningful size before 2005). Negative multiples do not make any economic sense because it is not possible to pay less than zero for a company. In addition, analysts always exclude negative multiples when they perform relative valuations. Hence, we ignore multiples with negative values. This exclusion does however result in a positive skewed data for the multiples, a situation we attempt to overcome by exploiting the fact that the logarithm of a random variable could move the variable towards a more normal-looking distribution.

### 7.3.2 ACCOUNTING RATIOS

The multiple driver analysis in section 6 identified profitability ratios and the risk section of section 5 uncovered several proxies for risk. These ratios and proxies, plus some additional relevant ratios were calculated from the prepared raw accounting data. Our selection process, focusing on theoretical relationships, reduces the possibility of data mining, and weaken the chance that any identified statistical significant relationships is not just found by pure luck, but as a result of a rigid analysis. It is also worth mentioning that by calculating the value drivers as ratios it is possible to compare and aggregate across the industry since ratios are not affected by size or currency.

Margin numbers like the EBIT, EBITDA, net profit, net operating profit after tax, operating cash flow and free cash flow, were all calculated as a percentage of sales. In order to be consistent with the multiples, all margins were based on trailing sales in the denominator and earnings were trailed in the nominator when calculating the earnings ratios. The cash flow margins are partly affected by balance sheet numbers like change in net working capital and capital expenditures, and were therefore calculated by adjusting the trailing earnings number with the relevant change in the balance sheet.

Return on equity was calculated as the trailing net profit divided by the book value of equity in both the E&P and dry bulk sector. Moreover, return on invested capital, which is commonly defined as operating profit after tax divided by invested capital (book value of equity plus book value of debt less cash), was applied normally with a trailing nominator when calculated the measure for all E&P companies. However, since it is virtually no taxes in the dry bulk sector, we applied a pre-tax return on invested capital, defined as EBIT divided by invested capital. Lastly, the capital intensity, formulated as depreciation divided by EBITDA, was calculated as the trailing depreciation number divided by the trailing EBITDA, while the reinvestment rate was calculated as capital expenditures less trailing depreciation plus change in net working capital as a percentage of operating profit after tax.

In our theoretical discussion on multiples, we discovered that all fundamental multiples were positively correlated to a future growth rate. At the same time, our analyses revealed that the analysts often ignore the cyclicality of cycle companies when they forecast earnings, extrapolating the current trend, which means that their forecasts might not be any better than a historical growth rate. A combination of this and lack of access to analysts' forecasts lead us to calculate and apply historical growth rates for a period of one, three and five years, in sales, net profit, operating profit after tax and book value of equity. In order to account for negative earnings, we estimate the growth rates by subtracting current earnings from previous earnings, and dividing this by the absolute number of the previous earnings.

The different risk measures, except beta, were formed from the retrieved accounting data. Profit margin risk was calculated as trailing operating expenditures divided by trailing sales revenue, while operating liability risk was created by using current liabilities as a proxy for operating liabilities and dividing that number with net operating assets. The last applied risk metric, financial leverage was estimated by dividing the book value of debt with the book value of equity.

### 7.3.3 ACCOUNTING PRACTICES

It should be noted that the ratios and multiples used in this thesis completely ignore accounting differences between the companies in the samples, a feature that can decrease the validity of our results because the ratios are not based on the same numbers. For instance, in the E&P sector, companies can either capitalise all exploration costs or only those which are considered to be successful, dependent on what method they use. However, it did not exist any information on accounting practices for the individual firms in the database and adjustments should thus have been done manually, a work we considered to be way over the scope of this thesis, given a sample of almost 700 companies.

### 7.3.4 ACCOUNTING RATIOS SUMMARY TABLE

**Figure 8.3.1 - Value drivers and accounting ratios as proxies**

| | | Value drivers | | | |
|---|---|---|---|---|---|
| | | Profitability | Cash Flow | Growth | Risk |
| Proxies | EBIT-margin | ✓ | | | |
| | EBITDA-margin | ✓ | ✓ | | |
| | NOPAT-margin | ✓ | | | |
| | OCF-margin | | ✓ | | |
| | FCFF-margin | | ✓ | | |
| | ROE | ✓ | | | |
| | ROIC | ✓ | | | |
| | Pre-tax ROIC | ✓ | | | |
| | 1-year growth[1] | | | ✓ | |
| | 3-year growth[1] | | | ✓ | |
| | 5-year growth[1] | | | ✓ | |
| | Capital intensity | ✓ | ✓ | | |
| | Reinvestment rate | | ✓ | | |
| | Beta | | | | ✓ |
| | Profit margin risk | ✓ | | | ✓ |
| | Op.liability risk | | | | ✓ |
| | D/E | | | | ✓ |

[1] This growth rate is calculated for sales, EBIT, NOPAT, net profit and book value of equity

Source: Own creation

The table above summaries all calculated accounting ratios, dividing them into proxies for profitability, cash flow, growth and/or risk, for later analysis.

# INDUSTRY LEVEL ANALYSIS ACROSS TIME

This section will apply our multiple and accounting ratios calculations to investigate how the fundamentals and multiples have behaved across time in the dry bulk and E&P sector by looking at the graphical relationships between the median multiples and median industry accounting ratios. In addition, the oil price and Baltic Dry Index, external factors assumed to be particularly important for the sectors, are graphed against the multiples and their price history are thoroughly evaluated.

## 8.1 SHIPPING

Trade has throughout history been an important driver for wealth and prosperity of nations, and due to the skewed distribution of natural resources shipping has served the world economy for over 5,000 years, providing a sophisticated transport service to every part of the globe. This was perfectly portrayed by Erling Næss, who once stated that God must have been a shipowner, since he placed the raw materials far from where they were needed and covered two thirds of the earth with water.

Despite its economic complexity, shipping's competitive nature and characteristics make the industry similar to the perfect market of classical economics. In this highly competitive environment there are three overall segments; bulk cargo, specialised cargo and general cargo. The bulk shipping industry advanced as the major sector in the decades following the Second World War, and emerged into two pillars, liquid bulk and dry bulk, which both transport large shiploads of a single raw material. General cargo or line shipping is however too small to justify a bulk operation, and of such a high value or delicateness that it requires a special shipping service for which the shippers prefer a fixed rate. Specialised shipping is somewhere between bulk shipping and liner shipping, but distinguishing itself by using ships specially designed to carry a specific cargo type targeted at a particular customer group. Within these segments dry bulk shipping is perhaps the most competitive and similar to the perfect market. As one of the most cyclical industries in the world, highly influenced by the relationship between the supply and demand, it is particularly fascinating to analyse and identify its value drivers (Stopford, 2008, pp. 64-66).

### 8.1.1 THE DRY BULK SECTOR AND THE FREIGHT RATES

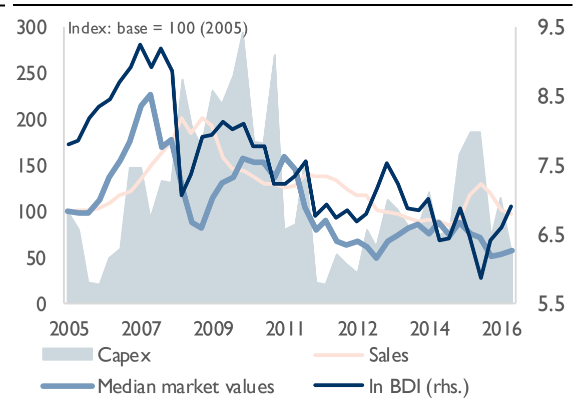
Dry bulk shipping is the transportation of unpackaged homogenous raw materials, such as iron ore, grain, coal, phosphates and bauxite, called major bulks, and cement, sugar, salt, forest products and chemicals, called minor bulks. These are products that are not only a part of our modern everyday lives, but also instrumental to the development of the global economy, through their role as a vital ingredient in building infrastructure and buildings. Thus, the dry bulk industry often coincides with the global business cycle's booms and busts. When the economy is growing more, investments are going into buildings and infrastructure, which requires raw materials such as cement, steel, iron ore and coal, driving the demand for dry bulk shipping, and vice versa in an economic deterioration. This is however only one side of the story, and the other side, supply, is also highly important for the dynamics in the industry. The amount a shipowner is paid (freight rates) depends on the availability or utilisation of vessels. Hence, a high demand for dry bulk transportation is not necessarily equivalent to high freight rates if the total number of ships available is abundant - reducing shipowners' bargaining power and the amount they are paid. This interaction between supply and demand in the dry bulk industry is perfectly illustrated in figure 8.1.1 below with the Baltic Dry Index.

Baltic Dry Index (BDI) measures the timecharter rates on 23 shipping routes, which is covered by dry bulk vessels carrying a range of raw materials, including coal, iron ore and grain. That is, the index provides an assessment of the price of moving the major dry bulk commodities by sea, which is a residual of the interaction between the supply and demand. Figure 8.1.2 shows how important the freight rates are for the industry economics and how closely the market follows when they price dry bulk companies. Despite an historically close relationship, market values seem to have disconnected from the freight rates the last four years, driven by a range of different factors that we will look into below.

**Figure 8.1.1 - Baltic Dry Index**


Source: Compustat and Bloomberg

**Figure 8.1.2 - BDI and indexed sector specifics**



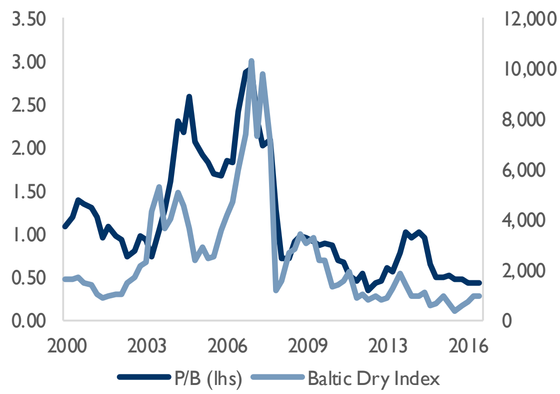

Source: Compustat and Bloomberg

After a descending period, the dry bulk market bottomed out in 1986, as displayed in the BDI chart figure 8.1.1, and freight rates advanced steadily to a new market peak in 1989, coinciding with a peak in the global business cycle. Over the next five years the dry bulk market witnessed a rare period where there was no clear cycle. Even though the world economy declined and went into a recession in 1992, dry bulk freight rates only took a brief dip, due to a surprisingly low addition of capacity, which subsequently lead to a recovery and a new peak in 1995. However, heavy investments were triggered during this market expansion, and when deliveries peaked in 1996 it sent the dry bulk market into a recession. Things got even worse when the Asia crisis triggered a recession in the Asian economies in June 1997, leading to a slumped growth and halting investments into the emerging Chinese economy. It was widely believed that a recovery would take several years, but during the next two years the market experienced a classic boom and bust cycle as the Asian economies only remained in recession for a few months. By the spring of 2000, industrial production was growing faster than ever. Unfortunately, it did not last too long, and the collapse of internet stocks in early 2001 set loose a deep recession all over the world.

The market bottomed in 2003 when China initiated a period of severe infrastructure development, which required tremendous quantities of raw materials. Between 2002 and 2007 China grew its steel production by over 200 pct., adding capacity equivalent to the amount produced in Europe, Japan and South Korea. This created an acute shortage of ships, which propelled freight rates to new highs and created one of the most extreme periods of dry bulk history. As bulk rates surged, ship ordering and ship building skyrocketed, evidently seen by the large increase in capital expenditures in figure 8.1.2, and the rates peaked in 2008 before the market crashed due to the financial crisis. The dry bulk market quickly recovered in an environment with persistent strong demand growth, but as an enormous amount of ships were beginning to be delivered (taking around three years to be build and delivered) and ship scrappings were low, the freight rates eventually plunged in mid-2010. Moreover, as the ship capacity remained extremely high, and investment and imports from China slowly haltered, the next seven years up to today have been characterised with low rates and a few short-lived rallies.

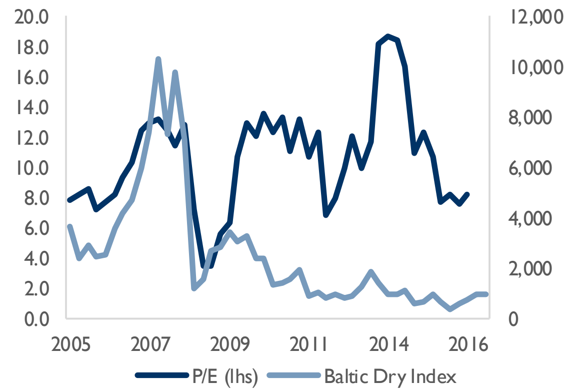
It is interesting to see how investors are over-extrapolating the duration and magnitude of these trends compared to what actually unfolds during the rallies. This is exactly what seems to have happened when the BDI witnessed a long awaited expansion in 2013/2014 and pricing multiples, such as P/E, went through the roof as a result of low earnings and investors extrapolating the trend too far. Another interesting aspect of the P/E ratio is how it seems to hover around a value of 10 quite consistently over the 10-year historical period in figure 8.1.4.

**Figure 8.1.3 - P/B on Baltic Dry Index**




Source: Compustat and Bloomberg

**Figure 8.1.4 - P/E on Baltic Dry Index**



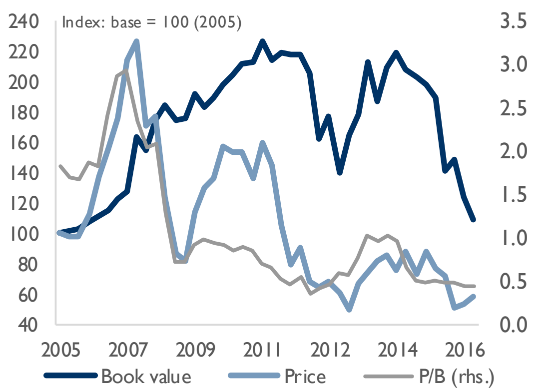

Source: Compustat and Bloomberg

P/B illustrates similar tendencies as P/E in the way that a small change in the BDI often is followed by an even larger reaction to the pricing multiple. However, P/B appear to follow BDI much more closely than P/E, which most likely is a consequence of the far less volatile nature of equity book values compared to earnings, making it possible for the price element in the P/B multiple to react more independently to changes in the BDI.

### 8.1.2 MULTIPLE BREAKDOWN

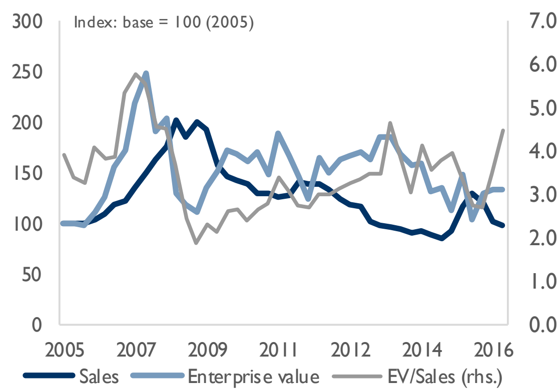
There is no doubt that the freight rates have an impact on the multiples in the dry bulk sector, both through the market values and through the industry economics. Figure 8.1.5 and Figure 8.1.6 dissects the P/B and EV/Sales multiple to see which element of the multiple that causes the changes. Looking at figure 8.1.5, it is easy to see that the increase in the P/B multiple leading up to the financial crisis was caused by faster growing market values than book values. The following crash in the freight rate index and the world economy, caused the price to drop steeply, while the book value actually continued to increase. This resulted in a massive downward correction in the P/B multiple. After a short upward correction in the market value caused by the uptick in the freight rates, the P/B multiple went into a week decline in the aftermath of the crisis, driven by growth in book value and a stagnant price. A stabilisation of the freight rates in 2011/2012 reduced the downward momentum in the price, increasing the P/B multiple in that period. Thereafter, the multiple corrects downward as the price drops faster than the book value. During the last couple of years, the multiple has stayed fairly flat due to evenly reductions in both the book value and the price.

**Figure 8.1.5 - P/B on indexed factors**




Source: Compustat and Bloomberg

**Figure 8.1.6 - EV/Sales on indexed factors**



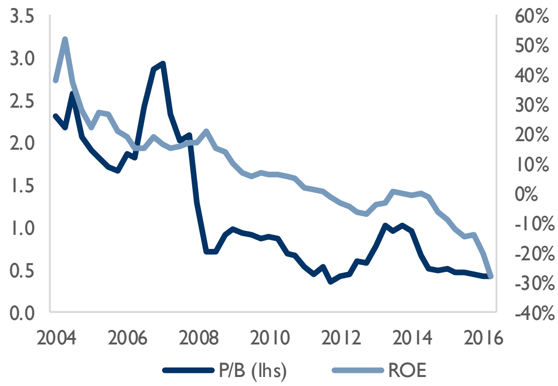

Source: Compustat and Bloomberg

The EV/Sales multiple in figure 8.1.6 is depicting the same trend leading up to and in the immediate aftermath of the financial crisis. However, the multiple is slowly increasing from 2010. This is driven by a somewhat flat trend in the enterprise value, while the sales figures have been decreasing with the freight rates, which may indicate that investors are looking past the current low freight rate environment and factor in better future prospects. The same features can be seen in the EV/EBITDA multiple in appendix 8.1 as well, but the rise in the multiple is more dramatic because EBITDA is falling at a faster rate than sales. The P/E multiple is rising and falling for the same reasons as the P/B and EV/Sales multiples the first years, but the multiple bounces quickly up to its pre-financial crisis level after the crisis, due to falling earnings and rising market values before it starts to stabilise. The P/E trades sideways at its historical levels for some time, but in 2014, rising market values and flat earnings creates a huge spike. It is clear that the price does not follows the development in earnings closely, as displayed in the P/E chart in appendix 8.1, and this causes large fluctuations in the P/E multiple.

### 8.1.3 PROFITABILITY

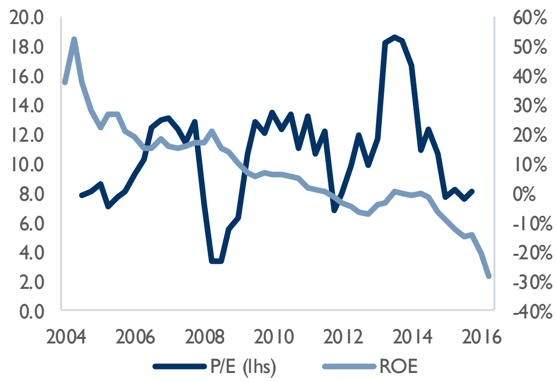
P/B and P/E appear to be driven by the dry bulk rates as illustrated in the charts above, but another important theoretical driver that was identified in a previous section is ROE. ROE has declined firmly since 2004, even when the market and earnings boomed between 2003 and 2008, signalling a strong downward trend in the profitability for dry bulk shipping companies. As seen in figure 8.1.7, P/B has tracked ROE reasonably well, both in the overall trend and through some rallies and downturns, but the relationship between P/E and ROE is more questionable. As already pointed out P/E has not demonstrated any clear trends, while ROE is clearly downward trending.

**Figure 8.1.7 - P/B on ROE**




Source: Compustat and Bloomberg

**Figure 8.1.8 - P/E on ROE**

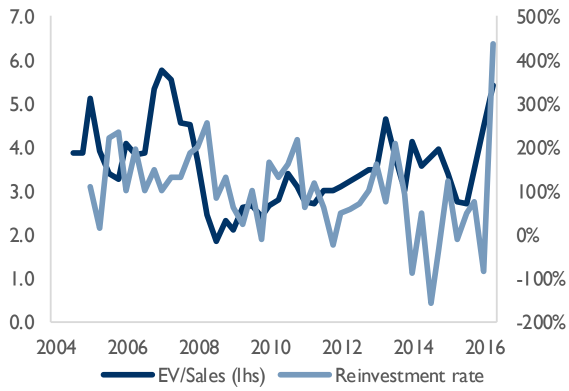



Source: Compustat and Bloomberg

ROIC and EBIT-margin has declined in a similar suit as ROE, illustrated in the two figures with EV/Sales and EV/EBITDA in appendix 8.1. Moving on to the reinvestment rate and capital intensity, an obvious point of interest is the inverse relationship between EV/Sales (figure 8.1.9), EV/EBITDA (appendix 8.1) and the reinvestment rate. As the EBIT-margin has been trending steadily downwards, much of the volatility in the reinvestment rate occur due to changes in non-current assets and net working capital. Thus, a potential explanation for the coinciding interaction is that investor and manager optimism arise at similar times, i.e. when dry bulk rates increase, investors buy dry bulk shares (pushing the multiples up), and managers are incentivised to invest in new ships. However, since the process of investing in new ships are much more time consuming than buying the companies' stocks, the effect is lagged, and leads to a negative relationship between EV/Sales and the reinvestment rate. No matter what, the relationship seems to be as proposed by theory; negative.

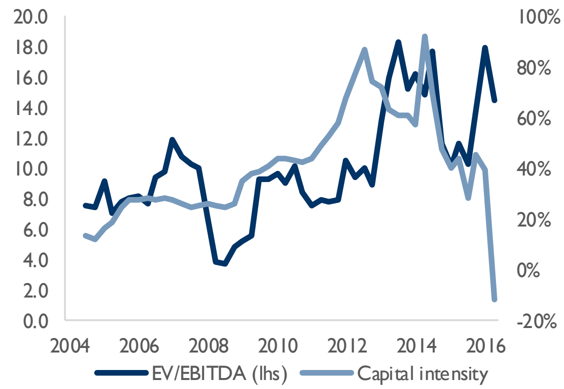
The relationship between EV/EBITDA and capital intensity in figure 8.1.10 is more peculiar. Both ratios appear to increase in tandem, but when the capital intensity raises it should, ceteris paribus, have a negative impact on EV/EBITDA. In this case, the downward trending industry EBITDA-margin can hold the explanation for the positive relationship, since a falling EBITDA will cause the capital intensity ratio to increase because of relatively fixed depreciation expenses, and the multiple to increase if the enterprise value is stable, which is partly confirmed by looking at the breakdown of the multiple in appendix 8.1.

**Figure 8.1.9 - EV/Sales on Reinvestment rate**




Source: Compustat and Bloomberg

**Figure 8.1.10 - EV/EBITDA on Capital intensity**

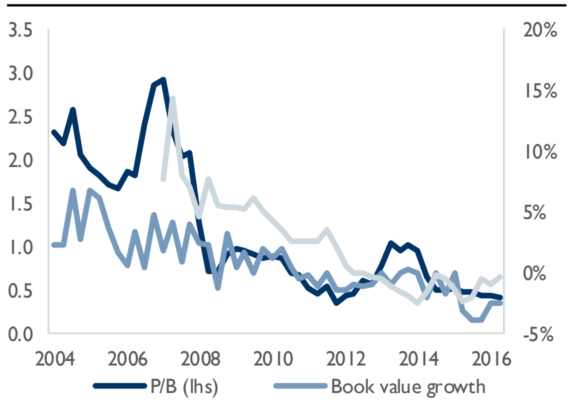



Source: Compustat and Bloomberg

### 8.1.4 GROWTH

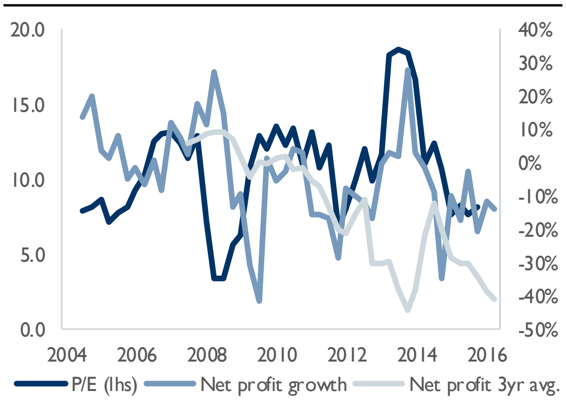
According to theory, book value and net profit growth are two important drivers of P/B and P/E and the EBIT growth is an important driver for the EV/Sales and EV/EBITDA multiples. P/E and net profit growth has experienced rather similar ups and downs, evidently seen in figure 8.1.12. At first, net profit growth lags the development in P/E, but over time the ratios have become more coherent. There seems to have been a tendency where investors have reacted to market movements, and after a couple of quarters this was materialised in the net profit as well. A similar pattern can also be observed in EV/Sales and EV/EBITDA against EBIT growth illustrated in appendix 8.1.

**Figure 8.1.11 - P/B on Book value growth**




Source: Compustat and Bloomberg

**Figure 8.1.12 - P/E on Net profit growth**



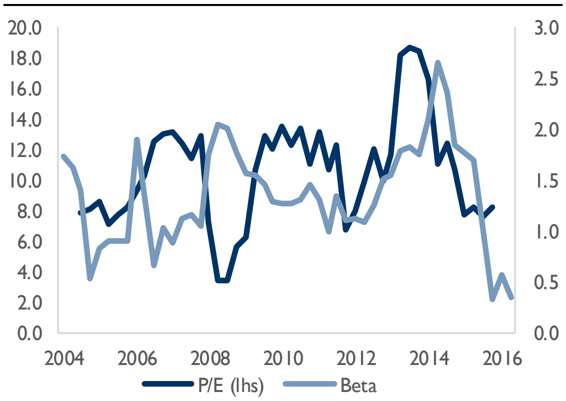

Source: Compustat and Bloomberg

Figure 8.1.11 confirms our previous assumptions on the fact that book value of equity is much less volatile than earnings – illustrated with a book value growth that remains close to zero most of the time, and very rarely moves over 5%. We saw in figure 8.1.5 that the industry market value and the industry book value moved pretty much in line from 2008 until 2012, which caused the multiple to be flat in that period. This is seen in figure 8.1.11 as well, while the detachment of the multiple and the book value growth in 2013/2014 is caused by a little uptick in the market value growth.

### 8.1.5 RISK

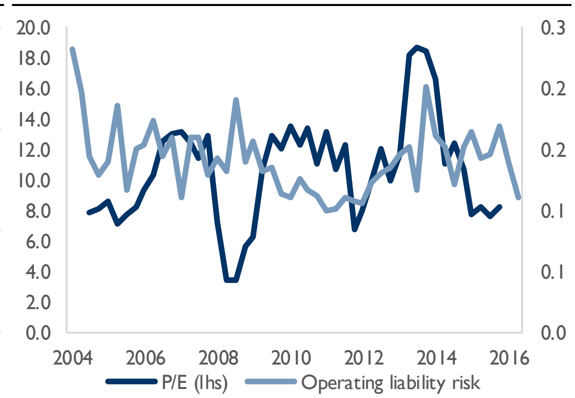
Beta, which is used as a proxy for risk, depicts an ambiguous relationship with the multiples. It seems to be both a positive and a negative driver for the EV/Sales, EV/EBITDA and the P/E multiple, see appendix 8.1. This ambiguous relationship is illustrated in figure 8.1.13, where the beta spikes in 2008 at the same time as the P/E multiple plummets and it spikes in 2014 when the multiple rises. The relationship seems to be more inversely when looking at the P/B multiple and beta in appendix 8.1. The operating liability risk in figure 8.1.14 similarly peaks around the same two areas, but has remained much more stable around a level of 0.15 over the period. It is however more ambiguous to explain why the operating liability risk increases when the P/E sharply declines or rises. One viable explanation could be that shipping companies extends it credit under pessimistic conditions, and buys more goods under credit in more optimistic conditions. Similar patterns on operating liability risk and beta for the other multiples are also present as displayed in appendix 8.1.

**Figure 8.1.13 - P/E on Beta**




Source: Compustat and Bloomberg

**Figure 8.1.14 - P/E on operating liability risk**

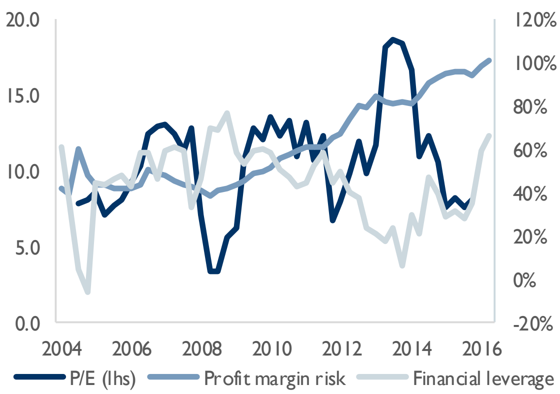



Source: Compustat and Bloomberg

P/E and financial leverage in figure 8.1.15 have an inverse relationship, most likely as a result of lower earnings and asset values during downturn periods, which lowers the equity book value and increases the financial leverage, and vice versa when the market is trending upwards. This is true if the price either increases or decreases relatively more than the shipping companies' earnings, so that the P/E ratio drops when earnings fall and rise when earnings increase. This negative relationship seems to be present when looking at the P/B multiple against financial leverage as well, as illustrated in appendix 8.1.

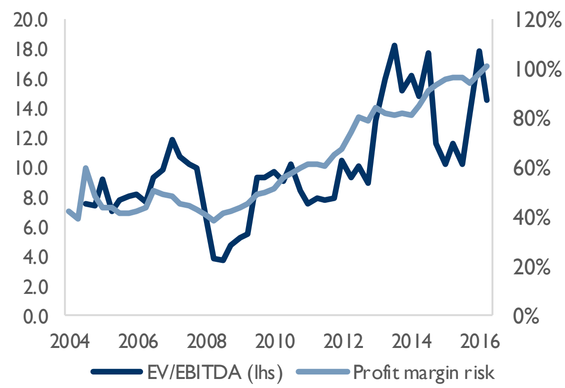
Profit margin risk has expanded steadily, obviously opposite to ROE and EBIT-margin, as increased operating expenses decrease ROE and EBIT-margin and increase the profit margin risk. There appears to be a positive trending relationship between EV/EBITDA and profit margin risk in figure 8.1.16, which provides us with a different story from what we observed in the P/E ratio in figure 8.1.15, where lower earnings seem to be offset by an even larger drop in the price. In this case, enterprise value seems to drop less than EBITDA, which could be a consequence of less volatile operating income than earnings or a subsequent increase in debt.

**Figure 8.1.15 - P/E on profit margin risk & leverage**




Source: Compustat and Bloomberg

**Figure 8.1.16 - EV/EBITDA on profit margin risk**




Source: Compustat and Bloomberg

### 8.1.6 HYPOTHESES REFINEMENT

After eyeballing and interpreting the graphical relationship between the multiples and the identified variables in the dry bulk industry, the initial hypothesis is refined and the bold font in figure 8.1.17 indicates a change from the initial hypothesis:

**Hypothesis 1.2 Dry bulk**

*There is a significant (…) relationship between the Y(n) and the X(n) in* figure 8.1.17

**Figure 8.1.17 - Hypothesis 1.2 Dry bulk**

| | Independent variable X (n) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 12 |
| Dependent variable Y (n) | ROE | ROIC | EBIT-margin | Growth | Capital intensity | Reinvestment rate | Beta | Profit margin risk | Op.liability risk | Debt to equity | Baltic Dry Index |
| 1 P/B | pos. | | | pos. | | | neg. | neg. | **pos/neg.** | neg. | pos. |
| 2 P/E | **pos/neg.** | | | pos. | | | **pos/neg.** | **unclear.** | **pos/neg.** | neg. | pos. |
| 3 EV/EBITDA | | **neg.** | | pos. | **pos.** | neg. | **pos/neg.** | **pos.** | **pos/neg.** | | **pos/neg.** |
| 4 EV/Sales | | **neg.** | **pos/neg.** | pos. | | neg. | **pos/neg.** | **pos.** | **pos/neg.** | | **pos/neg.** |

Source: Own creation

As seen in figure, there are drivers where the relationship seems to shift from positive to negative over the time period, which inspired us to formulate the second hypothesis:

**Hypothesis 2.1 Dry bulk**

*The relationship between the fundamentals and the multiples in the dry bulk sector are unstable across time*

Lastly, there seemed to exist a positive relationship between the Baltic Dry Index and the multiples, which encouraged us to formulate a third hypothesis:

**Hypothesis 3.1 Dry Bulk**

*There is a positive relationship between the Baltic Dry Index and the multiples in the dry bulk sector*

## 8.2 THE OIL INDUSTRY

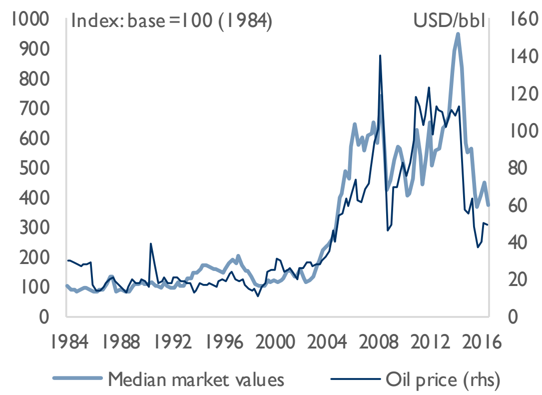
All of the oil and gas we use today stem from microscopic plants and creatures living in the ocean that absorbed energy from the sun million years ago, which was stored as carbon molecules in their living tissue. When they died, they sank to the bottom and were gradually buried deeper and deeper by layers of layers of sediment. Eventually, as a result of higher temperatures and rising pressure, oil and gas were formed (American Petroleum Institute, 2017). Oil is therefore the concentrated essence of many millions of years of ancient sunlight (Shah, 2008), which is brought back to life by a human's touch. The resurrection process is conducted by oil companies and supportive industries have risen to make the awakening process as efficient as possible.

Nowadays, the oil industry consists of three subsectors. The upstream sector is responsible for finding, lifting and processing oil and gas from the oil reservoirs and make it ready for transportation. This segment is commonly referred to as Exploration and Production (E&P). Second, the midstream sector is responsible for transportation and storage of crude oil and natural gas for further processing, usually conducted by pipelines, railroads, roads or tankers. Lastly, the downstream sector refines the oil into final products to end-consumers or raw material to be used by other industries, and is known as Refining and Marketing. In addition to these three main sectors, there exists a number of companies established to service the oil industry, ranging from seismic companies and drilling companies to companies specialized in transporting supplies to oil platforms. All of the companies in the oil industry have one thing in common, their activities are dependent on the same commodity. The difference is that both the midstream- and downstream sector are reliant on the upstream sector to strike oil to retain their purpose, while the upstream sector must find the oil. The E&P sector is thus the only segment that is "directly" exposed to the commodity, and given the fluctuation in the price of oil, it is interesting to see how these companies have fared historically.

### 8.2.1 THE E&P SECTOR AND THE OIL PRICE

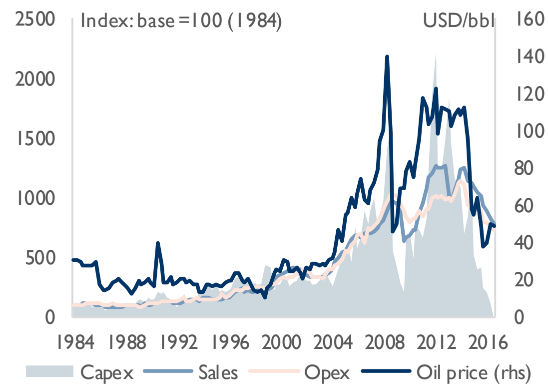
Every company delivers some kind of product or service to its customer, and E&P companies' ultimate product is crude oil. These companies sell their product, the oil, at prices regulated by the market. As a result, they are price takers in a market largely controlled by supply and demand, which implies that the E&P sector operates at the mercy of the oil price's volatile nature. This dependency creates extensive fluctuations in their market values and financial numbers and thus headache for people trying to forecast their future. Figure 8.2.1 and 8.2.2 display how the market values and the accounting numbers of E&P companies have moved with the oil price since the first quarter of 1984. The market values and accounting numbers of 37-45 E&P companies are indexed with 1984 as the base year, and the median of these indexed values each quarter is compared to the evolvement in the nominal average quarterly price per barrel of oil. If someone has ever wondered if the oil price drives the market values and economics of E&P companies, these graphs are worth a thousand words.

**Figure 8.2.1 - Oil price on E&P market values**




Source: Compustat and Bloomberg

**Figure 8.2.2 - Oil price on E&P accounting numbers**



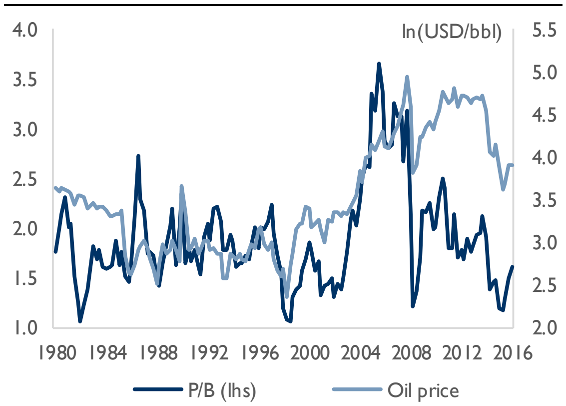

Source: Compustat and Bloomberg

Evidently seen by the graphs, the oil price is volatile and this volatility is transferred to the market values and the accounting numbers of the companies in the E&P sector. Over the graphed time period, the oil price has varied from 30 USD/bbl. in 1984, 140 USD/bbl. in 2008 to 37 USD/bbl. in 2015, with peaks and valleys along the way. Observe that the oil price does not follow an identifiable cyclical pattern in the sense of peaks and troughs in regularly time intervals, since supply, demand and sentiment take precedence over the cycles. It is disruption between the supply of oil and the demand for oil that forms the alpine oil price landscape, and there have been several periods of disruptions throughout history.

The oil price surged from 1973 until 1980, thanks to turbulence, like the Iranian revolution and the Iran-Iraq war, in the Middle East, the world's largest oil producing region (Hamiltion, 2011, pp. 16-17). It peaked in 1980 and declined steadily before it collapsed in 1985. The period with high oil prices had caused a change in the long-term demand for oil, and the collapse was initiated by a reduced demand for petroleum products (Hamiltion, 2011, p. 18). In 1990 the oil price spiked dramatically, triggered by Iraq's invasion of Kuwait and the ensuing Gulf Was, which caused supply disturbances. After the conflicts were resolved, the price declined sharply back to pre-conflict levels. From 1990 to 1997, global oil consumption increased by more than six millions of barrels per day (Speight & Fantacci, 2011, p. 162), and the price rose steady. However, the upturn come to an end because of a contraction in Asia, which reduced the demand, and increased production from the OPEC (a cartel of oil producing nations led by Saudi Arabia) created imbalance between demand and supply (Speight & Fantacci, 2011, p. 162).

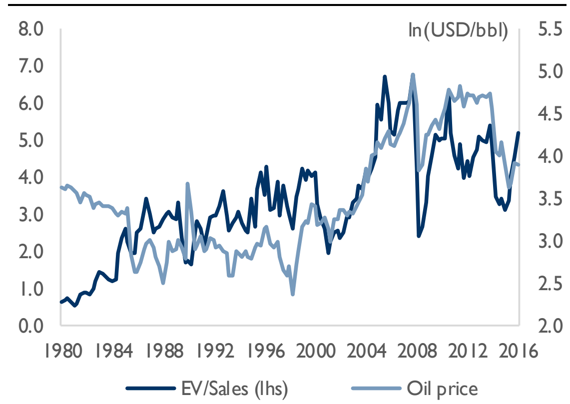
After the downturn, increased demand because of the industrialization of former agricultural economies and a significant decrease in OPEC supply, pushed the oil price considerably upwards to a record high price of 140 USD/bbl. in 2007/2008 (Hamiltion, 2011, pp. 18-19). A common saying states that all good things must come to an end, and the financial crisis made that saying truth. The crisis led to economic downturn and a sharply drop in demand, which hammered the oil price. The economic recovery in the aftermath of the crisis sent the price up again, and the price increased to over 100 USD/bbl. in 2011. The oil price hovered around 100-125 USD/bbl. until 2014, when the oil price was slashed by a series of "unfortunate" events. Several important economies, namely China, Russia, India and Brazil, experienced slower growth after 2010, a contrast to their greedy thirst for oil in the first decade of the 2000s, which reduced the demand. In the prelude to the oil price collapse, the shale oil revolution in the U.S. had reversed the long-standing decline in U.S. crude production and made the shale oil cost-competitive at the high oil prices. Combined with increased production from Canada's oil sands, these regions could now cut their oil imports, which put further downward pressure on the oil price. Lastly, as the price continued to drop, OPEC had the choice of defending market shares or reduce their production (and supply) to drive the price upwards again. OPEC chose to defend their market share at the expense of their role as a swing producer, which set the stage for a free fall. Today, almost three years later, the oil price has gained some terrain as OPEC has reduced their output in an attempt to act as a swing producer again, and a barrel of oil trades at approximately USD 55.

**Figure 8.2.3 - P/B on Oil price**




Source: Compustat and Bloomberg

**Figure 8.2.4 - EV/Sales on Oil price**




Source: Compustat and Bloomberg

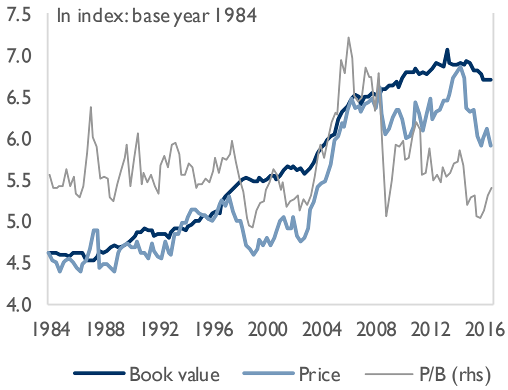
It is undoubtedly a close relationship between the E&P market values and the oil price, and figure 8.2.3 and 8.2.4 illustrates a similar connection between two pricing multiples and the oil price. Both the P/B and the EV/Sales multiple closely resemble the oil price with peaks and troughs that coincide fairly well. See appendix 8.2 for the P/E and EV/EBTIDA multiple.

### 8.2.2 MULTIPLE BREAKDOWN

Naturally, the oil price has an effect on how the multiples in the E&P sector behaves. Given the oil price's effect, it is useful to know if the change in the multiple is caused by a higher valuation, a reduction in the value driver or a combination of both. This gives increased knowledge about how investors act and react in a volatile oil environment.

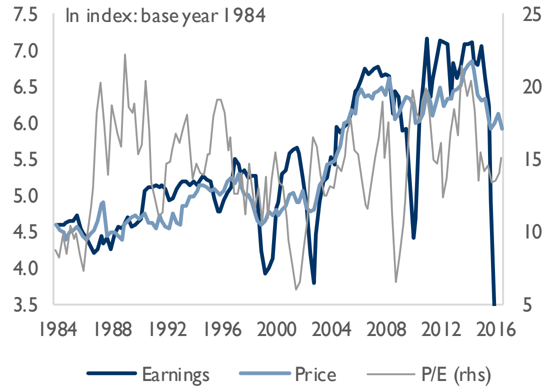
Figure 8.2.5 shows the median P/B multiple for the entire E&P sector against indexed market values and book values for companies with history going back to 1984. The median P/B multiple over the complete period is 1.79, indicating that the market on average expect the sector to earn more than the cost of equity, but it has fluctuated a lot. Both the book value and the market value followed each other closely from 1984 until 1997. Consequently, the P/B multiple moved sideways over that period. The peaks and troughs are caused by fluctuations in the market value and to a lesser degree changes in the book value, since book values have increased steadily over the period. In 1997, the market value and the book value clearly disconnect, which creates a dramatic drop in the P/B multiple. This coincides with the oil price crisis in 1997, and investors are visibly adjusting their valuations downward to reflect low oil prices, while the book values are flattening out. There is a significant turnaround in the market's valuation of the E&P sector in 2003. The oil price is surging, and the market value increases much faster than the book value, which propels the P/B multiple to record heights. However, the market value is slowing down in 2006, growing in line with the book value, and the multiple is therefore moving sideways until the financial crisis in 2008. When the financial crisis kicks in, the market value detaches from the book value again, throwing the multiple off the cliff. The oil price comeback in the aftermath leads to an upward, but bumpy, trend in the market price and the multiple corrects some of the lost ground, while the oil price collapse in 2014 leads to a faster deterioration of stock values than book values, which lowers the P/B multiple back to levels seen right after the financial crisis. The EV/Sales and EV/EBITDA multiples in appendix 8.2 show a similar pattern as the P/B multiple, but the EV/EBITDA multiple has more of the cyclicality seen in the P/E multiple in figure 8.2.6.

**Figure 8.2.5 - P/B on Indexed factors**




Source: Compustat and Bloomberg

**Figure 8.2.6 - P/E on Indexed factors**



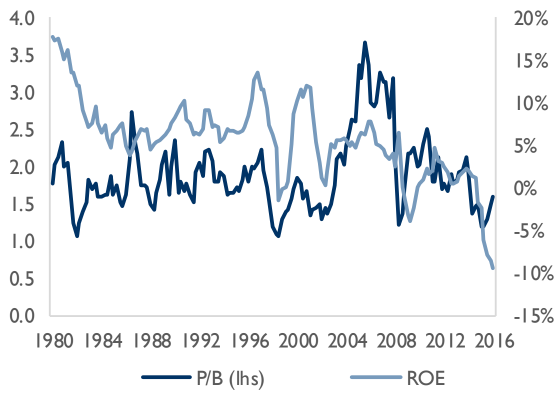

Source: Compustat and Bloomberg

Figure 8.2.6 displays the E&P sector's P/E multiple over the same period, and the overall median P/E multiple is 14.6. The multiple is even more volatile than the P/B multiple since earnings are extremely sensitive to changes in the oil price. This multiple looks more like the illustrative figure 5.6, with several periods of an inverse relationship between the P/E multiple and the earnings. Note how the market appears to look through the plunges in earnings in 1996, 1998, 2002, the plunge caused by the financial crisis and the earnings downturn in the aftermath of the 2014 price drop, as well as the earnings peak in 2001. This ignorance of earnings creates spikes in the multiple when earnings are at the lowest, and a very low multiple when earnings peak. However, the earnings lag the oil price, and the market follows the development in the oil price closely, which means that the oil price has turned before the earnings bottom out and that the market is pricing in the higher oil price. The long-lived upturn in the oil price from 2002/2003 sent both earnings and market values up in the sky, but the market value tampered off as soon as the oil price showed sign of reversion in 2006, making the multiple plummet down. The oil price recovered quickly and traded sideways until June 2014, followed by the market value. Small changes in the oil price that period, caused the earnings to spike and fall several times and the multiple to bounce up and down. The oil price collapse three years ago put pressure on the multiple once again as market prices reacted fast to the new low oil price environment. See appendix 8.2 for the price, earnings and the oil price in the same graph.

### 8.2.3 PROFITABILITY

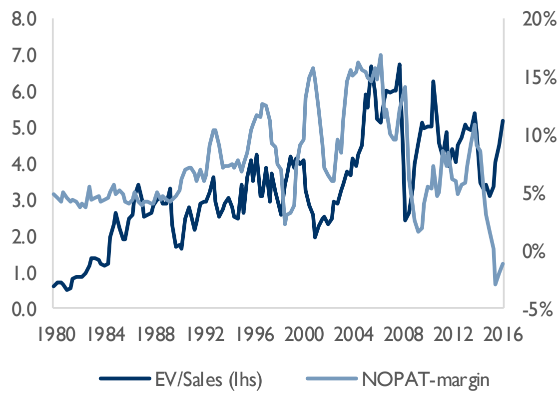
The multiple analysis in section 6 uncovered a list of key theoretical drivers for each multiple. Return on equity was identified as the most prominent profitability driver for the P/B multiple, while the after tax operating (NOPAT)-margin was an important driver for the EV/Sales multiple. Graphically, the relationship between ROE and the P/B multiple seems to be relevant in the E&P sector as well, illustrated in figure 8.2.7, where the P/B multiple and ROE appears to track each other fairly well, but the magnitude of the increase in ROE is much smaller than the increase in the multiple in the early 2000's when the oil price surges. Similarly, the NOPAT-margin in figure 8.2.8 seems to influence the EV/Sales multiple.

**Figure 8.2.7 - P/B on ROE**




Source: Compustat and Bloomberg

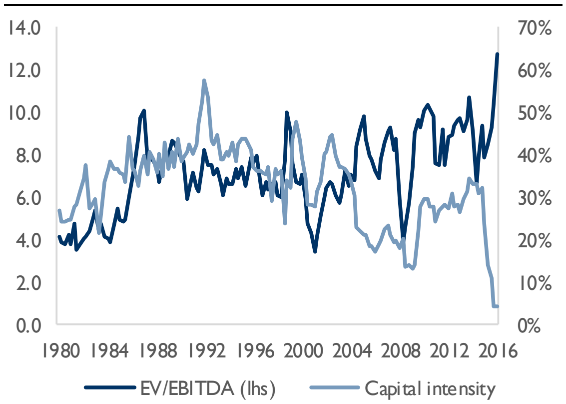
**Figure 8.2.8 - EV/Sales on After tax op.margin**




Source: Compustat and Bloomberg

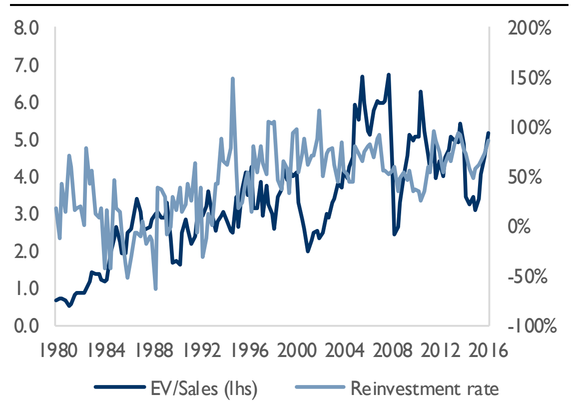
The relationship is more unstable between the return on invested capital (ROIC) and the EV/Sales multiple as seen in appendix 8.2. In contrast to the connection between ROE, NOPAT-margin and the above multiples, appendix 8.2 depicts an inverse pattern between ROIC and the EV/EBITDA multiple, and between ROE and the P/E multiple, which seems to be in line with the illustrative multiple graph in figure 5.4.3.

**Figure 8.2.9 - EV/EBITDA on capital intensity**




Source: Compustat and Bloomberg

**Figure 8.2.10 - EV/Sales on Reinvestment rate**



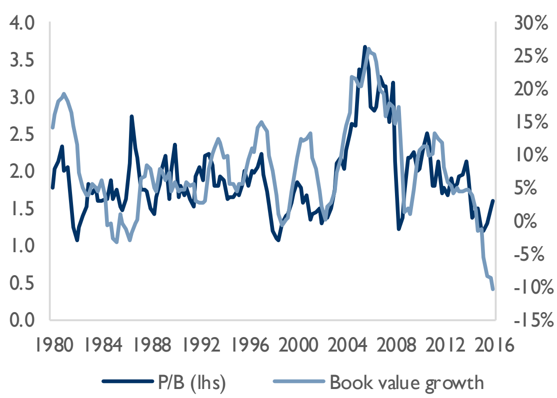

Source: Compustat and Bloomberg

Higher capital intensity should theoretically have a negative effect on the EV/EBITDA multiple, because it increases the EBITDA in the denominator. However, the illustrated relationship in figure 8.2.9 is ambiguous. There are periods where the relationship seems to hold, for example in 2001-2004 the capital intensity is falling while the multiple is increasing, but there are periods where the opposite is true as well. Higher reinvestment reduces the cash flow and was identified as a negative contributor to the EV/EBITDA multiple. It is not easy to decipher the relationship between these two variables in figure 8.2.10, but if we put on our strongest eyeglasses, there seem to be an inverse relationship between the two.

### 8.2.4 GROWTH

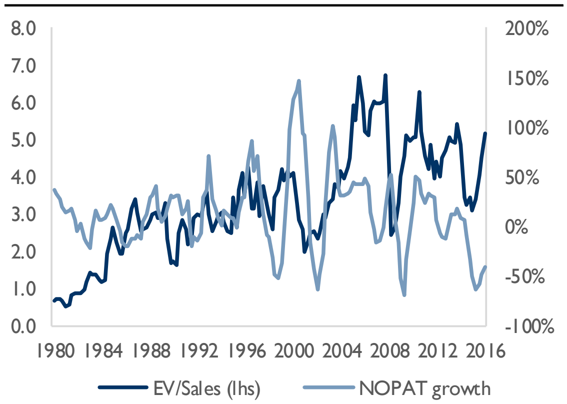
Unlike the growth rate in the dry bulk sector, the median book value growth in the E&P sector is fluctuating up and down around 7%. There seems to be a close connection between the historical one-year book value growth rate and the P/B multiple, clearly seen in figure 8.1.11. The link between the EV/Sales multiple and the one-year NOPAT growth do not show the same close connection. There is undoubtedly some covariation, but the NOPAT growth seems to lag the multiple. This may indicate that the market is pricing in the growth before it materialises, which supports the idea that investors are incorporating future growth prospects in their price.

**Figure 8.2.11 - P/B on Book value growth**




Source: Compustat and Bloomberg

**Figure 8.2.12 - EV/Sales on NOPAT growth**

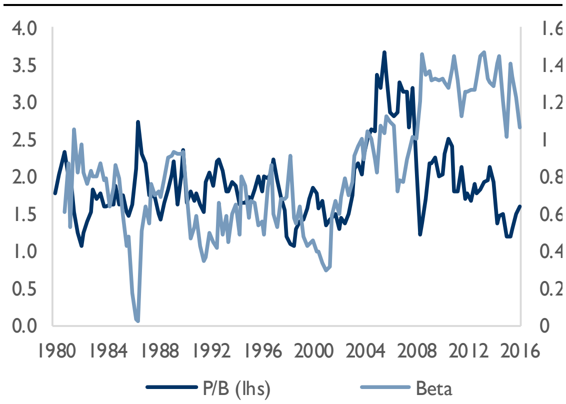



Source: Compustat and Bloomberg

Appendix 8.2 show the link between net profit growth and NOPAT growth, and the P/E multiple and the EV/EBITDA multiple respectively, portraying the same pattern as seen in figure 8.2.12.

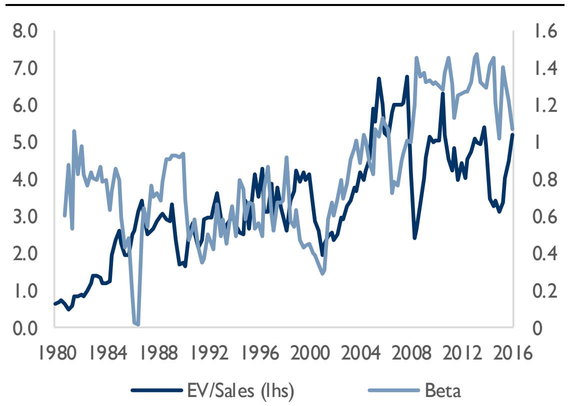
### 8.2.5 RISK

**Figure 8.2.13 - P/B on Beta**




Source: Compustat and Bloomberg

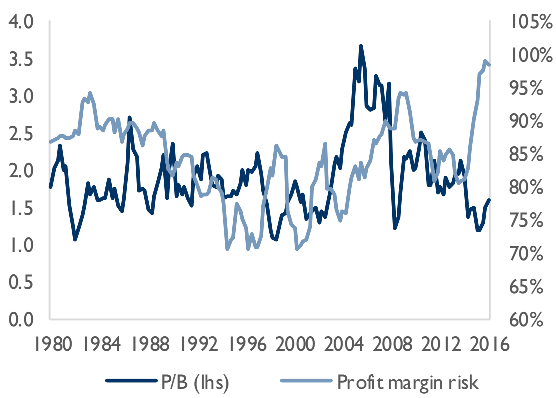
**Figure 8.2.14 - EV/Sales on Beta**




Source: Compustat and Bloomberg

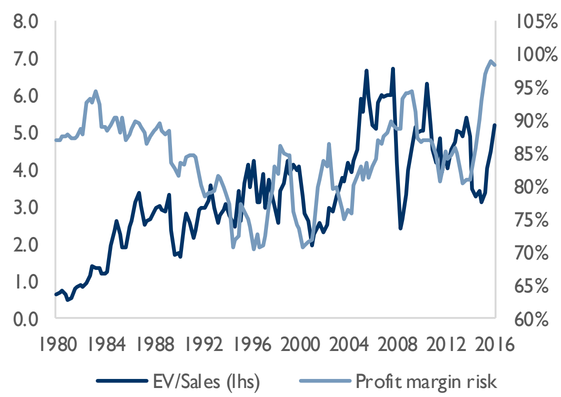
Beta were previously described as a way of measuring the riskiness of the stock. According to the multiple analysis, higher risk should result in a lower multiple. Figure 8.2.13 and 8.2.14 graphs the median sector beta on the P/B and the P/E multiple. Until the oil price turnaround in 2001/2002, beta and both the multiples seem to be somewhat inversely related. However, from 2002 and to the end of 2004 both beta and the multiples are rising in tandem, opposite of what is expected. At the end of this two-year period, beta disconnects from the multiples and the inversely related relationship looks like it has been established again. The same development can be seen when graphing beta against the EV/EBITDA and the P/E multiple (see appendix 8.2).

**Figure 8.2.15 - P/B on Profit margin risk**




Source: Compustat and Bloomberg

**Figure 8.2.16 - EV/Sales on Profit margin risk**




Source: Compustat and Bloomberg

A higher ratio of operational expenditures as a percentage of sales, which may be due to higher labour costs or service costs per dollar of sale, and thus a higher ROE risk, seems to be followed by a lower multiple in figure 8.2.15 and 8.2.16. Higher risk should put pressure on the multiple, and the tendency seen in the graphs are therefore as expected. The same pattern can be seen when looking at the other multiples as well (see appendix 8.2). In appendix 8.2 the financial leverage ratio and the operating liability risk are graphed against all the multiples. The operating liabilities as a percentage of net operating assets, have been fairly stable throughout the entire time period, but it exhibits constantly small fluctuations in the short term. It is not possible to attach any meaning to the relationship just by looking at the graph.

### 8.2.6 HYPOTHESES REFINEMENT

After eyeballing and interpreting the graphical relationship between the multiples and the identified variables in the E&P industry, the initial hypothesis is refined where the bold font in figure 8.2.17 indicates a change from the initial hypothesis:

**Hypothesis 1.3 E&P**

*There is a significant (…) relationship between the Y(n) and the X(n) in figure 8.2.17*

**Figure 8.2.17 - Hypothesis 1.3: E&P**

| | | Independent variable X (n) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 12 |
| n | | ROE | ROIC | NOPAT-margin | Growth | Capital intensity | Reinvestment rate | Beta | Profit margin risk | Op.liability risk | Debt to equity | Oil price |
| Dependent variable Y 1 | P/B | pos. | | | pos. | | | **pos/neg.** | neg. | **unclear** | **pos/neg.** | pos. |
| 2 | P/E | **neg.** | | | **neg.** | | | **pos/neg.** | **pos/neg.** | **unclear** | **pos/neg.** | pos. |
| 3 | EV/EBITDA | | **neg.** | | **neg.** | **pos/neg.** | neg. | **pos/neg.** | **pos/neg.** | **unclear** | | **pos/neg.** |
| 4 | EV/Sales | | **pos/neg.** | pos. | **pos/neg.** | | neg. | **pos/neg.** | **pos/neg.** | **unclear** | | **neg.** |

Source: Own creation

As seen in the figure, there are drivers where the relationship seems to shift from positive to negative over the time period. This inspired us to formulate the second hypothesis:

**Hypothesis 2.1 E&P**

*The relationship between the fundamentals and the multiples in the E&P sector are unstable across time*

Lastly, the oil price and the multiples looked like they were positive correlated and this encouraged us to formulate a third hypothesis:

**Hypothesis 3.1 E&P**

*There is a positive relationship between the oil price and the multiples in the E&P sector*

# REGRESSION ANALYSIS

The descriptive industry analysis in section 8 illustrated the graphical relationship between the multiples and the variables deemed to be economic significant for the multiple. A simple graph is useful to get a quick overview and sense of how variables have moved together over time. However, to get a really in-depth understanding of the relationship beyond what the eye can process and to test the proposed hypotheses, it is prudent to extend the analysis with a regression.

The regression analysis has the power to quantify the magnitude, the direction and the significance of the relationship between the multiples and the key drivers, but also the ability to provide a model that can value a company and a sector based on the estimated coefficients. This section will therefore establish two regression models for each multiple, where the initial regression is purely based on the identified drivers in the theory section, and the second one is a refinement of the initial model where we remove/include variables after an economic and statistical assessment of the relevant variables. The regression results will be used to answer the hypotheses presented in the previous sections.

## 9.1 MODEL SPECIFICATIONS AND ASSUMPTIONS

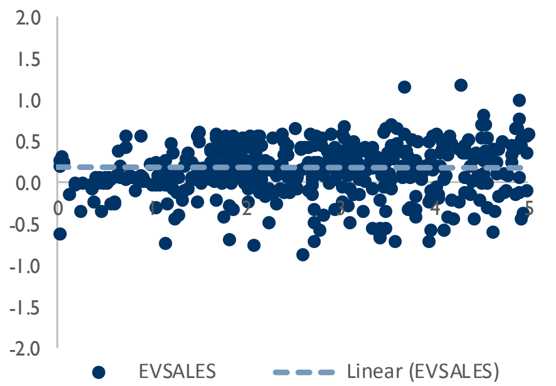
Our regression model is based on the linear framework discussed in the regression theory passage, due to its simple and flexible nature. It allows both explanatory and dependent variables to be transformed in any way, and can therefore handle non-linear relationships. A multi-linear regression model is structured around the four dependent variables, ln P/B, ln P/E, ln EV/Sales and ln EV/EBITDA, and implemented in each available quarter in several quarterly cross-sectional regressions and in an overall pooled cross-sectional regression for each multiple.

### 9.1.1 LINEARITY

A basic assumption in the linear regression model is that the relationship between explanatory variables and the dependent variable is additive and follow a normal distribution. However, the relationship may be exponential, or even multiplicative, which would require a logarithmic transformation of the dependent variable, or both the covariates and the dependent variable, respectively (Nau, 2017). The latter option is nevertheless not optimal due to the fact that a large fraction of our explanatory variables take on negative values. A logarithmic transformation of both our dependent and independent variables would thus reduce our dataset significantly. Consequently, this points in the direction of a transformation of only the dependent variable.

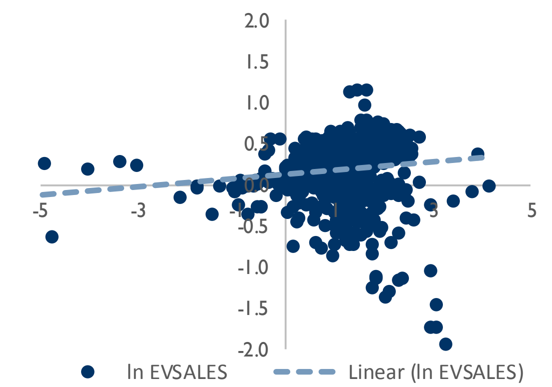
As already mentioned, our dependent variables are strictly positive, and taking the logarithm of these values could ease the threat of heterogeneity and create a more normal-looking distribution (Acosta-Calzado, Acosta-Calzado, & Murrieta-Romo, 2010, p. 14). In our endeavour to uncover the relationship between the covariates and the dependent variable, we have performed a sample of univariate regression and bivariate scatterplots in both the oil and dry bulk industry. As displayed in figure 9.1.1, where EV/Sales is plotted against the EBIT-margin, there appears to be no linear relationship between the two variables, but when we add the logarithm on EV/Sales, a weak positive relationship between EV/Sales and the EBIT-margin is formed. These patterns can also be observed in other variables, such as EV/Sales plotted against Beta in appendix 9.1, which demonstrates a fairly strong negative linear relationship when EV/Sales undergoes a logarithmic transformation. Hence, we argue that the dependent variable grows or decays exponentially as a function of the explanatory variables, justifying our decision to transform all dependent variables in our data set. It also worth mentioning that we apply the natural logarithm to the multiples (although all log functions yield the same linear scaling), because small changes in the natural logarithm are equivalent to percentage changes (Nau, 2017).

**Figure 9.1.1 - EV/Sales on EBIT-margin**




Source: Own creation

**Figure 9.1.2 - ln EV/Sales on EBIT-margin**




Source: Own creation

### 9.1.2 HOMOSCEDASTICITY

Another important assumption in the linear regression model involves the variance of the error term. A model is said to exhibit homogeneity if the error is constant across different values of explanatory variables and the dependent variable. If this is not true, and the model experiences heteroscedasticity, it can lead to standard deviations and confidence intervals that are too wide or too narrow. Especially if the variance is increasing over time (the "fanning effect"), the prediction interval will tend to be unrealistically narrow. Increasing variance may also have the effect of giving too much weight to a small part of the data set when estimating coefficients, particularly the subset where the error variance is the largest (Nau, 2017).

Gurajati (2004) gives some examples of why heteroscedasticity can arise. He explains that heteroscedasticity can emerge as people learn and their errors of behaviour become smaller over time or through a growing discretionary income, which give people more choices, increasing the variance as income rise. However, more importantly for our analysis, is the fact that outliers, skewness and incorrect data transformation can create heteroscedasticity and alter the results of our regression analysis extensively (Gujarati, 2004, pp. 390,391). The two latter issues were exactly what we were trying to solve in the previous section, and in accordance to previous research, if it does not fully remove heteroscedasticity, it should at least reduce the effect. In terms of the former, we have quite a few outliers that could be elimination candidates, and after careful analysis, some outlier variables that were clearly a flaw have either been corrected or removed. However, one should be extremely careful when considering to remove outliers, and it would require more information on the specific outliers and a whole new set of analyses if we were to remove more of the outliers. We believe that some outliers could contain relevant information to the analysis, and that the transformations in the prior section assisted in restoring assumptions and reducing the impact from extreme values. Thus, we argue that no additional outliers should be removed from the sample in the risk of venturing into data mining and losing valuable information, but highlight that it may impact some of the assumptions negatively.

In our hunt for heteroscedasticity we have performed both a Breusch-Pagan (BP) test and a White test, in order to cross-check our results, even though they should yield similar conclusions as our regression models do not contain any non-linear relationships. Having said that, the figure below actually displays that BP and White contradict each other on every single multiple in the dry bulk sector.

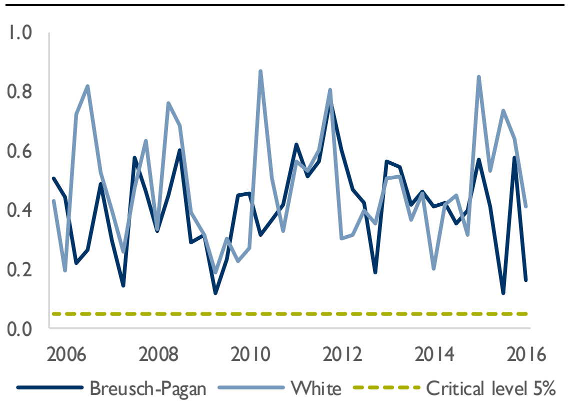
**Figure 9.1.3 - Homoskedasticity tests on poole data in Dry Bulk and E&P**

| | ln EVSALES | | ln EVEBITDA | | ln PB | | ln PE | |
|---|---|---|---|---|---|---|---|---|
| | White | BP | White | BP | White | BP | White | BP |
| **Dry Bulk** | 1.93 | 16.35 *** | 1.23 | 10.4 *** | 0.06 | 4.30 ** | NA | NA |
| **E&P** | 2.11 | 1.58 | 23.30 *** | 10.1 *** | 1144 *** | 134 *** | 134 *** | 3.78 ** |

Source: Own creation Significance level: *** 0.01 ** 0.05 * 0.1

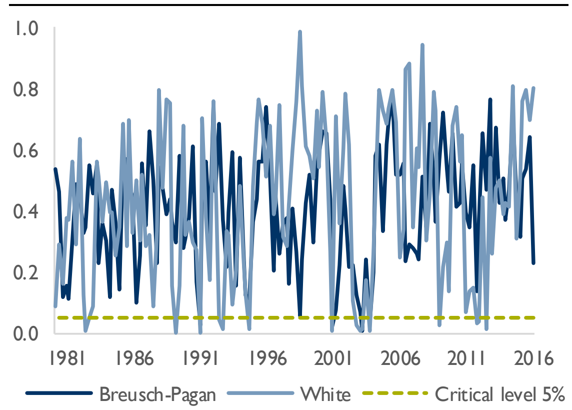
Despite our efforts to remove or reduce any heteroscedasticity, there still appears to be some heteroscedasticity present in the regression analyses performed on the two industries. Figure 9.1.3 presents the results from our BP and White tests for the overall pooled cross sectional regression. A significant BP or White test means that the null-hypothesis on homoscedasticity are rejected. While BP demonstrates heteroscedasticity in the pooled dry bulk regression, White presents the opposite conclusion. However, if we also take a look at the tests in figure 9.1.4, which tests the quarterly cross sectional regressions, there does not seem to be any heteroscedasticity at all. Although this chart only displays the quarterly regressions for ln EV/Sales regressions in dry bulk, similar patterns are observed in the other regressions as well, illustrated in appendix 9.1.

**Figure 9.1.4 - BP and White on ln EVSALES Dry Bulk**




Source: Own creation

**Figure 9.1.5 - BP and White on EVSALES E&P**

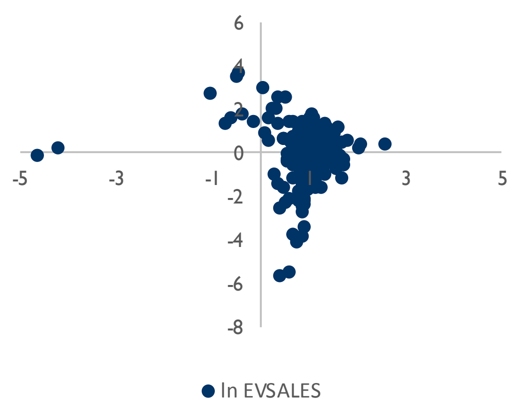



Source: Own creation

Except for the pooled EV/Sales regression, all pooled oil regressions indicate heteroscedasticity, and mostly at an 1% significance level. Still, the quarterly EV/Sales regressions in figure 9.1.5 only demonstrates a few significant test results, and similarly to dry bulk, this is also observed in the other multiples regressions.

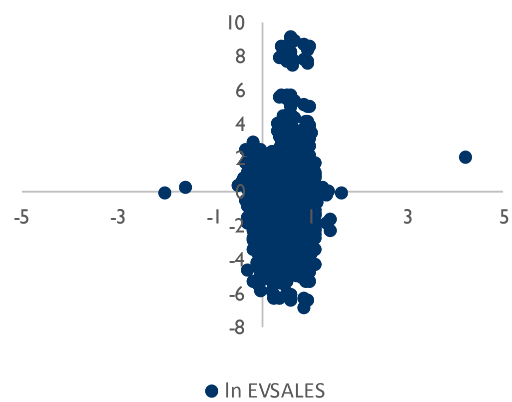
The pooled predicted EV/Sales on residuals in figure 9.1.6 shows an apparent stable error variance, which further confirms our beliefs. Thus, the homoscedasticity assumption appears to be valid in the dry bulk sample, but some of the BP test still demonstrate heteroscedasticity, both pooled and quarterly for the other regressions. It is more difficult to not reject the homoscedasticity assumption in the oil sample, where the results are much more ambiguous. The pooled regressions indicate fairly strong heteroscedasticity, but in the quarterly regressions the issue appears surprisingly mild. Despite highly significant tests in the pooled oil regressions, the plot with predicted EV/Sales against residuals below in figure 9.1.7 and similar plots from the oil sample displayed in appendix 9.1, all demonstrate fairly stable variance of the error term. This could however be a result of coefficients with low economic significance. Nonetheless, we generate heteroscedasticity-consistent standard errors for both oil and dry bulk regressions to be cautious, even though the heteroscedasticity appears to be fairly modest in the dry bulk sample.

**Figure 9.1.6 - Predicted Dry Bulk & residuals**




Source: Own creation

**Figure 9.1.7 - Predicted E&P & residuals**




Source: Own creation

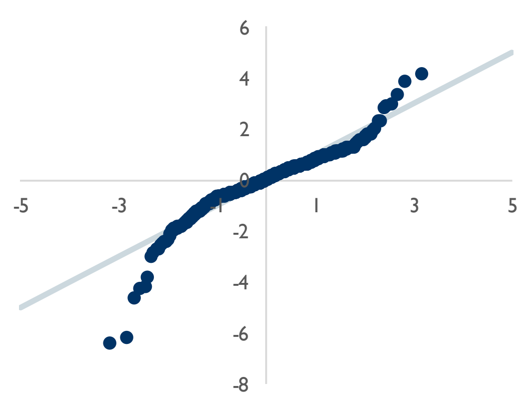
We apply the HCCME method introduced by White (1980), and apply the correction factor known as $HC_2$, which reduces the bias due to points of high leverage (Zaiontz, 2017). Some argues that $HC_3$ produces superior results to $HC_2$, and that the more recent approach $HC_4$ can be superior to $HC_3$. However, we performed several tests with all three approaches, and $HC_3$ and $HC_4$ yielded us very extreme estimates of the standard error. There is of course a chance that the extreme estimates are justified, but we find it overly unstable. Thus, in conformity with Davidson and MacKinnon and Barreto and Howland (2005), we stick with $HC_2$ as the correction factor for the HCCME method.

### 9.1.3 NORMALITY

Nau (2017) writes that a normally distributed sample or normally distributed residuals is not paramount if you are willing to assume that the linear model and the coefficients you have estimated are correct, and your objective is to produce predictions. But generally, he states, we are also interested in examining the robustness of the model and constructing confidence and prediction intervals, in which case the normal distribution assumption is important.

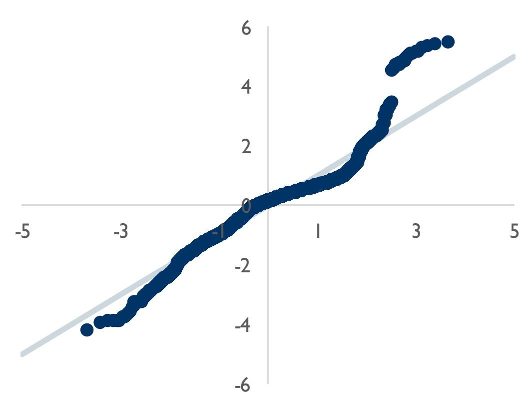
A violation of the normality assumptions creates problems when evaluating whether a coefficient is statistical significant or not. Commonly, the error distribution will be skewed if the data contains a few large outliers. As already discussed, there appears to be some outliers in our sample, and if we examine the two charts below, figure 9.1.8 and 9.1.9, they seem to confirm our suspicions. The Q-Q plot for the EV/Sales regression residuals in dry bulk displays a S-shaped pattern of deviations, indicating excessive kurtosis, which means that there are either too many or too few large errors in both directions (Nau, 2017). One could also argue that there is somewhat of a right-skewed distribution with too many large errors on the right side. For the EV/Sales E&P regression there is more of a left-skewed characteristic, but for the rest of the Q-Q plots in the oil sample there are more S-shaped patterns. These other oil plots are illustrated in appendix 9.1 together with the other dry bulk plots, which too a greater extent share similar characteristics as the dry bulk EV/Sales Q-Q plot.

**Figure 9.1.8 - Q-Q plot EV/Sales Dry Bulk residuals**




Source: Own creation

**Figure 9.1.9 - Q-Q plot EV/Sales E&P residuals**




Source: Own creation

Our observations are further confirmed by examining figure 9.4.3 with Jarque-Barre (JB) test and D'Agostino-Pearson (DP) test implemented on the pooled data set. Not surprisingly, JB and DP tests, which both are based on the skewness and kurtosis of the data sample, present us with the same conclusion as above. All tests are significant at a 1 pct. level, which means that the null-hypothesis on normality is rejected.

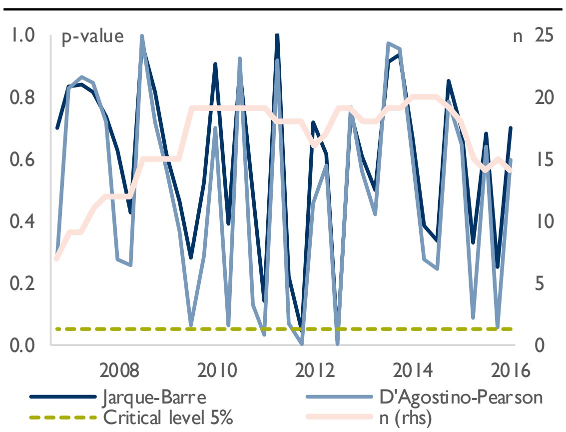
**Figure 9.1.10 - Normality tests on pooled data in Dry Bulk and E&P**

| | ln EVSALES | | ln EVEBITDA | | ln PB | | ln PE | |
|---|---|---|---|---|---|---|---|---|
| | JB | DP | JB | DP | JB | DP | JB | DP |
| **Dry Bulk** | 1363 *** | 1372 *** | 891 *** | 899 *** | 125 *** | 126 *** | NA | NA |
| **E&P** | 2602 *** | 2605 *** | 36936 *** | 36982 *** | 8338 *** | 126 *** | 8724 *** | 8732 *** |

Source: Own creation     Significance level: *** 0.01   ** 0.05   * 0.1

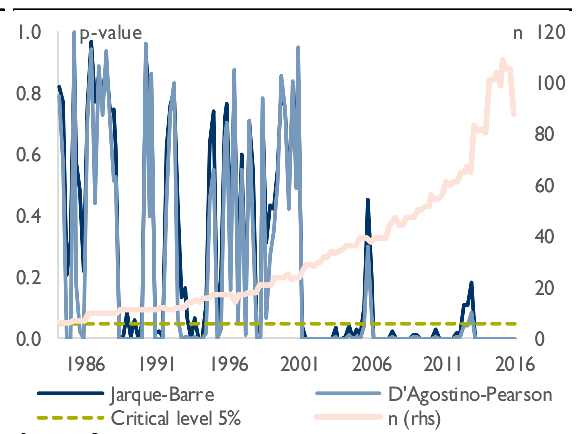
Despite the gruelling results, Nau (2017) explains that a large sample size, such as the one on E&P, regularly will fail the normality tests even though there is only a small deviation from normality. This could perhaps explain why the quarterly normality tests in the EV/Sales E&P regression in figure 9.1.12 starts off by accepting normality, but as the sample size begins to increase from 2002, the normality tests fails. It also does not make sense if we bring in the central limit theorem, where one would assume normality if the sample size is large enough. In other words, the sum of an increasing sample size with independent and identically distributed random variables would, according to the central limit theorem, gravitate towards a normal distribution (Nau, 2017). Interestingly enough, our JB and DP tests in the quarterly dry bulk regression produce mostly insignificant results as displayed in figure 9.1.11, leading us to assume normality. This is surprising, because the sample sizes in the quarterly dry bulk regressions are a lot smaller, making it more difficult to justify a normal distribution according to the central limit theorem. However, opposite to the large sample sizes, Nau writes that a small sample size will commonly pass the normality tests due to limited power to reject the null-hypothesis. Consequently, we should be cautious when interpreting the significance levels, and confidence and prediction intervals in the quarterly dry bulk regression, while the pooled dry bulk and oil regressions, as well as the quarterly oil regressions are more prudent if we take central limit theorem in to account.

**Figure 9.1.11 - JB and DP on ln EV/Sales Dry Bulk**




Source: Own creation

**Figure 9.1.12 - JB and DP on ln EV/Sales E&P**

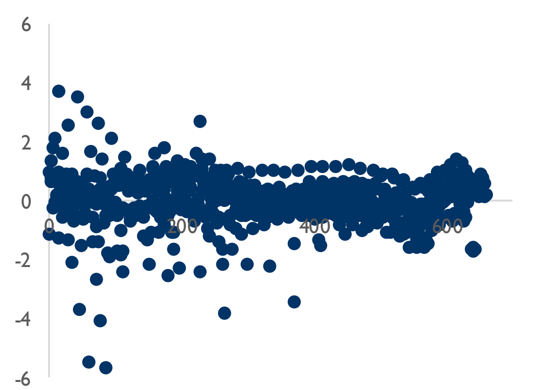



Source: Own creation

### 9.1.4 INDEPENDENCE

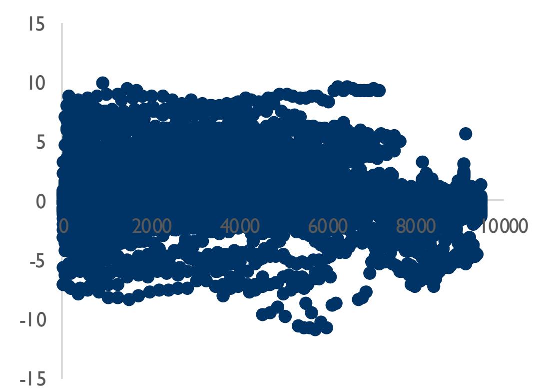
Statistical independence between the error terms may not be of great importance to our cross-sectional data samples, but it is a highly relevant issue to consider when studying pooled data and the central limit theorem discussed above. In order to investigate into this matter, residuals from the pooled EV/Sales regressions are plotted against the row numbers as illustrated in figure 9.1.13 for dry bulk and figure 9.1.14 for E&P. Most notably, there appears to be no form of systemic underpredictions or overpredictions to either of the plots. Hence, the residuals seem randomly distributed around the centre line, underpinning the assumption of statistical independence between the errors. A similar conclusion can also be drawn from the other residuals and row number plots found in appendix 9.1.

**Figure 9.1.13 - EV/Sales Dry Bulk residuals & row #**




Source: Own creation

**Figure 9.1.14 - EV/Sales E&P residuals & row #**




Source: Own creation

### 9.1.5 ENDOGENEITY

Endogeneity comes in many different forms, although the principle is the same – the residual is correlated with an explanatory variable. Of these various forms of endogeneity, it is likely that our data suffers from survivorship bias, or sample selection bias, even though we have tried to minimise it by including every single company in the relevant sectors whether or not they are currently trading, have been acquired, delisted or gone bankrupt. Another highly relevant issue, is omitted variable bias. Obviously, the solution here is to include the missing variable, which is what we are trying to control for by performing our refinement process, such as including the oil price and BDI. We will however not experiment with instrument variables and the two-stage least squares model, remaining confident that our refinement process is sufficient

### 9.1.6 MULTICOLLINEARITY

As all our numbers are derived from the same location – stock prices, balance sheet, income statement and cash flow statement – there are bound to be some multicollinearity present. The preferred rule of thumb is to obtain more data, but since our data sets more or less contain all exchange traded companies within the specific sector, it is not possible to get more data. However, because we screen through our models with VIF and CI, we remove any indication of severe multicollinearity immediately. Despite the risk of losing information, we are not concerned because most of the collinear variables tell the same story.

### 9.1.7 CONCLUSIVE THOUGHTS ON MODEL SPECIFICATIONS AND ASSUMPTIONS

This section has disclosed how our multi-linear regression model performs when we test for its underlying assumptions. In our case, an increasing or decreasing variance across observations and extreme outliers are the primary issues that can seriously flaw our results. We have attempted to control for this and the additivity assumption by transforming our dependent variable and removing clearly faulted outliers. Despite our efforts to reduce heteroscedasticity and restore normality, all assumptions do not appear to hold for every regression. Consequently, we apply heteroscedasticity-consistent standard errors, and rely on the central limit theorem in the pooled E&P and dry bulk regressions, as well as the quarterly E&P regressions, while we should be more caution when interpreting the quarterly dry bulk regression results. Nevertheless, it should be taken into account that the predictions, confidence intervals and scientific insights yielded by our regression model may be inefficient and seriously biased or misleading because the regression appears to violate some assumptions from time to time.

## 9.2 INITIAL REGRESSION RESULTS AND ANALYSIS

Our initial model is based on a regression with variables identified by our theoretical framework in section 6, where key multiple drivers where derived from fundamentals. Multicollinear variables are removed from the regression, but variables are still kept in the model whether or not they are economical or statistical significant. In this process the ln P/E multiple in dry bulk is discarded from any further testing due to a very low number of observations as a consequence of challenging market conditions and negative earnings in the sector, i.e. negative multiples that are automatically removed from the sample.

### 9.2.1 E&P INDUSTRY

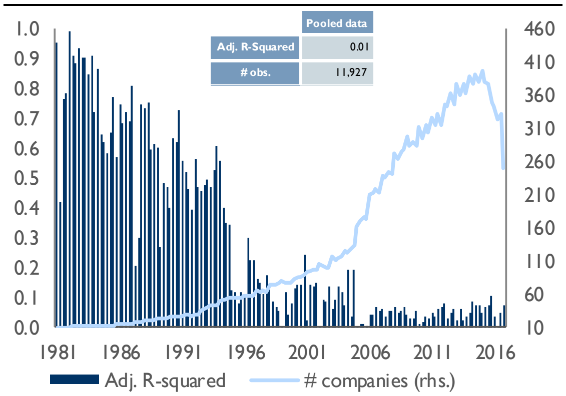
The quarterly cross-sectional regressions are conducted each quarter from 1981 until the fourth quarter of 2016, while the pooled cross-sectional regressions are conducted over the entire time period. Variables depicting a high degree of multicollinearity are removed from the regression because they distort the estimated coefficients and make them unreliable, which means that the initial regressions may be missing some of the earlier identified drivers.

#### ln P/B regression

##### *Model evaluation and summary statistics*

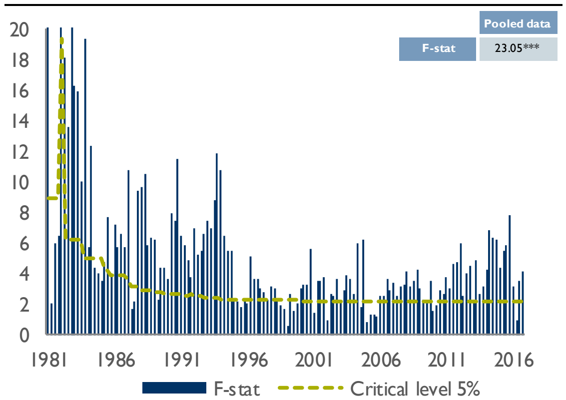
The ln P/B multiple is regressed on ROE, book value growth, beta, profit margin risk, operating liability risk and debt-to-equity. Figure 9.2.2 show the quarterly adjusted R-squared and the number of companies in the sample at each quarter. The figure clearly shows that the explanatory power of the model has decreased dramatically the last two decades, while the sample size has increased over the period. There can be many explanations for this pattern, but some possibilities may be that investors have lost interest or confidence in accounting ratios when assessing E&P companies' values, that the larger sample size actually forces the adjusted R-squared closer to the "true" explanatory degree of the model (Frost, 2014) or a combination of the two.  The median adjusted R-squared over the entire period is 0.14, while the pooled cross sectional regression with 11,927 observations yields a marginally low adjusted r-squared of 0.01 and a standard error of 2.3, indicating that the pooled model would yield highly uncertain predictions.

**Figure 9.2.2 - Adjusted R-squared & sample size**




Source: Own creation

**Figure 9.2.3 - Joint significance test**




Source: Own creation

Figure 9.2.3 tests the joint significance of the coefficients in the model. The graph shows that the F-stat is crossing the critical level several quarters, more specifically 113 out of 144 quarters, implying that the coefficients are jointly significantly different from zero most of the time, which is further confirmed by the high F-stat in the pooled regression.

The industry analysis uncovered both volatile multiples and accounting ratios over the examined time period. Volatility is also a key factor when looking at the summary statistics from the regressions in figure 9.2.4. As seen in the table, there is a large dispersion between the minimum, median and maximum levels of the coefficients and the standard errors of the model. All coefficients have a negative minimum value and a positive maximum value, a feature that discloses the instability of the coefficients and the fact that they can take on different signs throughout the period. Moreover, the quarterly data reveals that the intercept and ROE are the ones most statistical significant over the period with 78 and 97 significantly quarters of a total of 144 quarters, respectively. The number of significant quarters for the other coefficients range from 14 for the 1-year book value growth to 32 for the debt-to-equity ratio. That said, the key drivers' median coefficients are all showing the expected sign except for the D/E ratio. However, the positive D/E ratio makes sense if the leverage in the industry is favourable, i.e. a positive spread between ROE and cost of debt.

When we look at the pooled regression, there is actually only two statistical significant variables, namely the intercept and the beta coefficient. ROE, which appeared to be the most important coefficient in the light of the quarterly regressions, is surprisingly enough now insignificant. It is also worth mentioning that even though beta is statistical significant with a negative sign as expected, its economic significance is limited.

**Figure 9.2.4 - Summary statistics for ln P/B regressions**

**Quarterly data**

| Adjusted R-squared | | | R-squared | CI† |
|---|---|---|---|---|
| Min. | Median | Max. | Median | #/total |
| -0.03 | 0.14 | 0.99 | 0.20 | 40/144 |

| Std. Error of Estimate | | | F-test | |
|---|---|---|---|---|
| Min. | Median | Max. | Avg. | # sig./total |
| 0.05 | 1.47 | 2.61 | 3,78 | 0/144 |

| | Min. | Median | Max. | # sig./total | # VIF‡/total |
|---|---|---|---|---|---|
| Intercept | -1.78 | 0.78 | 2.09 | 0/144 | n.a. |
| ROE | -6.34 | 0.29 | 5.90 | 0/144 | 4/144 |
| Book value growth | -3.98 | 0.01 | 4.85 | 0/144 | 1/144 |
| Beta | -1.76 | -0.02 | 0.97 | 0/144 | 1/144 |
| Profit margin risk | -4.32 | 0.00 | 1.97 | 0/144 | 0/144 |
| Operating liability risk | -3.33 | 0.01 | 1.98 | 0/144 | 2/144 |
| Debt to equity | -0.88 | 0.07 | 2.25 | 0/144 | 3/144 |

# sig/.total: Number of significant quarters of total (95% conf. level)

†: number of quarters with moderate to strong multicollinarity/value of condition index. Strong to moderate multicollinarity when 100<CI<1000

‡: quarters (#) with multicollinarity/variable is highly multicollinare when VIF>10

**Pooled data**

| # sample size | Adj. R-squared | F-test | Std.Error | CI† |
|---|---|---|---|---|
| 11,927 | 0.01 | 23,05*** | 2.34 | 26.46 |

| | Coef. | VIF‡ |
|---|---|---|
| Intercept | 1,05*** | n.a. |
| ROE | 0.008 | 1.02 |
| Book value growth | -0.0001 | 1.00 |
| Beta | -0,004*** | 1.00 |
| Profit margin risk | 0.0001 | 1.00 |
| Operating liab. risk | -0.0002 | 1.00 |
| Debt to equity | 0.0008 | 1.02 |

*Significant at 90 % confidence level.

**Significant at 95 % confidence level.

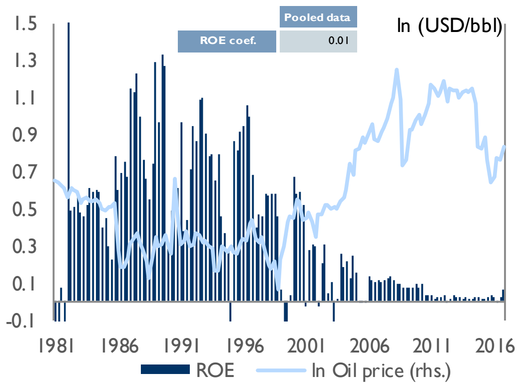
***Significant at 99 % confidence level.

Source: Own Creation

### *Analysis of selected regression coefficient over time*

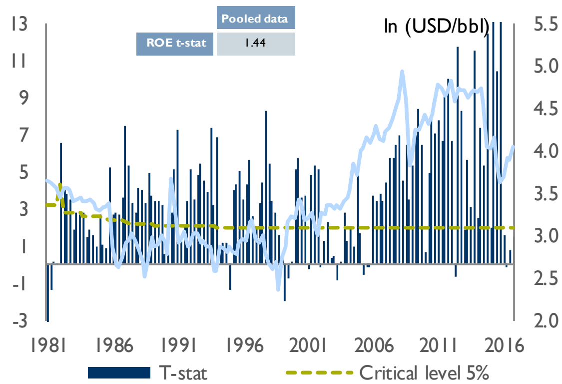
Return on equity seemed to be the most significant variable over time, thus it is interesting to see in what direction it affects the multiple and how the relationship has evolved. Two things come to mind when we look at the level of the coefficient over time in figure 9.2.5. First, the sign of the coefficient is mostly as predicted by theory, positive, with only a few negative quarters, which implies that investors reward companies with a higher ROE. Second, the estimated coefficients are depicting a sideways and fluctuating trend until early 2000s when a negative trend is materialising itself, and prevailing until today. In other words, investors are "paying" less for an increase in the return on equity today than they did 16 years ago.

**Figure 9.2.5 - ROE coef. & Oil price over time**




Source: Own creation

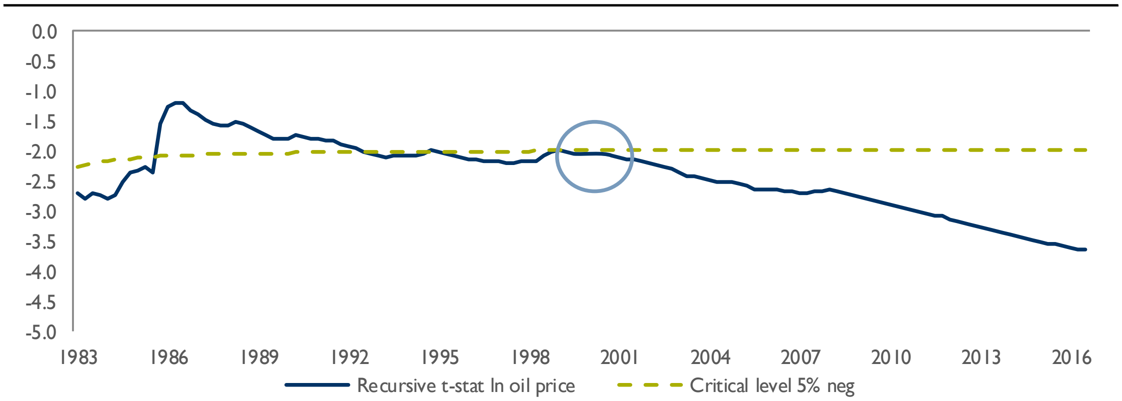
**Figure 9.2.6 - ROE t-stat & ln Oil price**




Source: Own creation

The oil price is included in the same graph to interpret the coefficient in the context of the prevailing oil price environment. Interestingly, the coefficient drops to a much lower level and is sliding downwards at the same time as the oil price is starting its seven-year climb to record highs of 140 USD/barrel. Thus, it may be inferred that the high oil price environment from the early 2000s has contributed to a rotation away from accounting returns in terms of how much investors are willing to pay for them. T-stats from recursive regressions of the coefficients on the oil price over the entire period confirm the observation. As seen in Figure 9.2.7, the t-stat crosses the critical level at the same point in time as the coefficient is starting to fall, which indicates that the relationship between the coefficient and the oil price becomes more negative significantly robust from that point in time.

**Figure 9.2.7 - T-stat from recursive regressions of ROE coefficients on ln oil price**




Source: Own creation

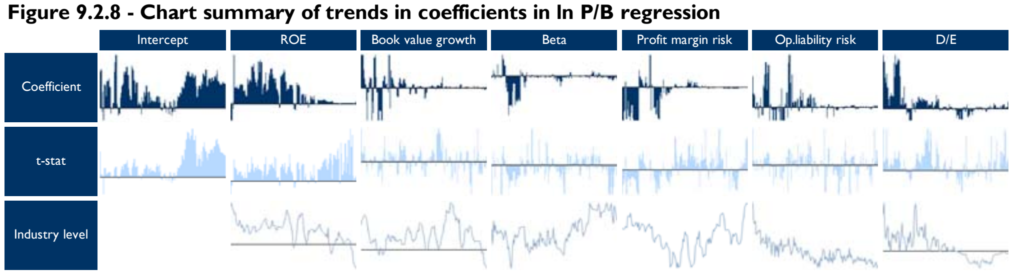
About the same time as investors are starting to throw less money at additional return on equity, the median return on equity in the industry is also deteriorating, as seen in Figure 8.2.7 in the industry analysis. The coefficient in this regression therefore suggests, at least the last 16 years and when we are adjusting for a simultaneous change in the other predictors in the model, that investors pay less for an increase in return on equity in an environment where oil prices are surging and the industry ROE is crumbling.

Figure 9.2.6 tracks the significance level of the coefficient over the same time period. There seem to be a pattern where the coefficient is significantly positive when the oil price is increasing and less significant when it is falling, thus it is coinciding with the oil price cycle fairly well. As a result, it can be concluded that an oil price hike seems to increase the statistically significance of ROE at the expense of its economic significance.

### *Trend summary of all regression coefficients*

Figure 9.2.7 displays the evolvement of all coefficients in the regression over the entire period. As with the ROE coefficient, there is an overall trend that the estimated coefficient becomes less economically significant after the oil price hike in the early 2000s. This may be translated into a general statement that investors now are less fixated about fundamentals, expressed as historical accounting ratios, and more focused on the oil price. The coefficient and t-stat graphs illustrate the prevalent volatility in the coefficients and significance levels, and reveal the shifting signs of the coefficients, while the industry level graph shows the corresponding trend in median industry levels analysed in section 8. See appendix 9.2 for more detailed graphs per coefficient.

**Figure 9.2.8 - Chart summary of trends in coefficients in ln P/B regression**



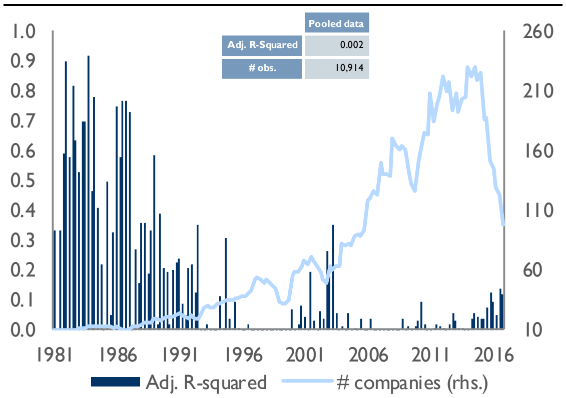

Source: Own creation

## ln P/E regression

### *Model evaluation and summary statistics*

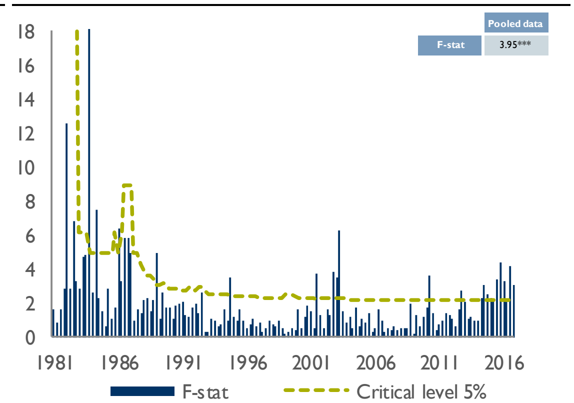
The ln P/E-multiple is regressed on ROE, earnings growth, beta, profit margin risk, operating liability risk and debt-to-equity. Compared to the P/B regression, the adjusted R-squared collapsed ten years earlier in the ln P/E model, seen in figure 9.2.9. Since then, the explanatory power has been almost completely absent, except for a period from 2001 to 2003, and signs of an uptick in the last couple of quarters. The median adjusted R-squared over the entire period is 0.03, while the ratio is even lower for the pooled cross-sectional regression. Whereas the joint significance test for the P/B regression depicted a resilient model, the opposite is true for the P/E-regression. As seen in figure 9.2.10, there is few significant quarters. The coefficients are only joint significant in 21 of 144 quarters, which make the model untrustworthy. On the other hand, when performing the pooled cross sectional regression, the F-stat indicates that the coefficients are jointly significantly different from zero.

**Figure 9.2.9 - Adjusted R-squared & sample size**




Source: Own creation

**Figure 9.2.10 - Joint significance test**




Source: Own creation

The summary statistics in figure 9.2.11 expose the weak relationship between the P/E multiple and the fundamentals. The coefficients are seldom statistically different from zero over the period, where ROE is the most frequently significant coefficient with only 28 significant quarters followed by beta with 23 significant quarters. The median ROE coefficient in the quarterly regressions is negative, which contradicts the economic theory and the positive sign seen in the P/B model. However, this is in line with the inverse relationship we saw in the industry analysis. Similarly, the median earnings growth rate coefficient is negative and in line with the graphical relationship illustrated earlier as well. The pooled cross sectional model indicates that both the ROE and the operating liability risk is significantly negative, while the profit margin risk is significantly positive. All the significant coefficients take on the opposite sign of what is predicted by the economic theory, but this may not be completely off if we take into account section 5.4 about cyclical valuation and the industry analysis. Since there is no particular coefficient that stands out as significant in terms of number of quarters, a detailed analysis of a selected coefficient is omitted.

**Figure 9.2.11 - Summary statistics ln P/E regression**

**Quarterly data**

| Adjusted R-squared | | | R-squared | CI† |
|---|---|---|---|---|
| Min. | Median | Max. | Median | #/total |
| -0.24 | 0.03 | 0.92 | 0.13 | 31/144 |

| Std. Error of Estimate | | | F-test | |
|---|---|---|---|---|
| Min. | Median | Max. | Avg. | # sig./total |
| 0.14 | 1.52 | 3.02 | 1,39 | 0/144 |

| Variable | Min. | Median | Max. | # sig./total | # VIF‡/total |
|---|---|---|---|---|---|
| Intercept | -1.11 | 2.98 | 6.45 | 0/144 | n.a. |
| ROE | -6.46 | -0.04 | 6.15 | 0/144 | 2/144 |
| Earnings growth | -4.47 | -0.01 | 1.89 | 0/144 | 3/144 |
| Beta | -1.48 | -0.01 | 1.06 | 0/144 | 3/144 |
| Profit margin risk | -4.17 | -0.14 | 2.54 | 0/144 | 2/144 |
| Operating liability risk | -3.10 | -0.04 | 2.65 | 0/144 | 6/144 |
| Debt to equity | -0.81 | 0.10 | 3.96 | 0/144 | 2/144 |

# sig/.total: number of significant quarters of total (95% conf. level)

†: number of quarters with moderate to strong multicollinarity/value of condition index. Strong to moderate multicollinarity when 100<CI<1000

‡: quarters (#) with multicollinarity/variable is highly multicollinare when VIF>10

**Pooled data**

| # sample size | Adj. R-squared | F-test | Std.Error | CI† |
|---|---|---|---|---|
| 10,914 | 0.0016 | 3,95*** | 2.28 | 9.72 |

| Variable | Coef. | VIF‡ |
|---|---|---|
| Intercept | 2,98*** | n.a. |
| ROE | -0,004*** | 1.16 |
| Earnings growth | 0.0000 | 1.00 |
| Beta | -0,001 | 1.00 |
| Profit margin risk | 0,005** | 1.00 |
| Operating liab. risk | -0,001** | 1.00 |
| Debt to equity | 0.0001 | 1.16 |

*Significant at 90 % confidence level.

**Significant at 95 % confidence level.

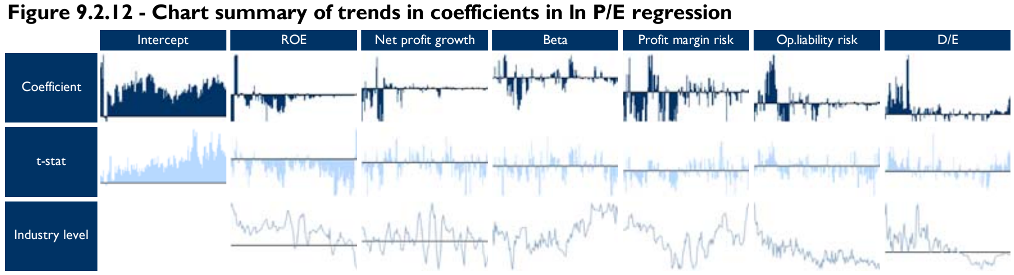
***Significant at 99 % confidence level.

Source: Own Creation

### *Trend summary of all regression coefficients*

After a quick glance at the coefficient charts in figure 9.2.12 it is tempting to conclude that the magnitude of the coefficients is tapering off exactly at the same time as it did in the ln P/B regression. However, the statistical significance of the variables is in general not present, which mean that we cannot reject the null hypothesis that the coefficients were not different from zero before the rotation happened, which greatly reduces the power of the above observation. See appendix 9.2 for more detailed graphs per coefficient.

**Figure 9.2.12 - Chart summary of trends in coefficients in ln P/E regression**



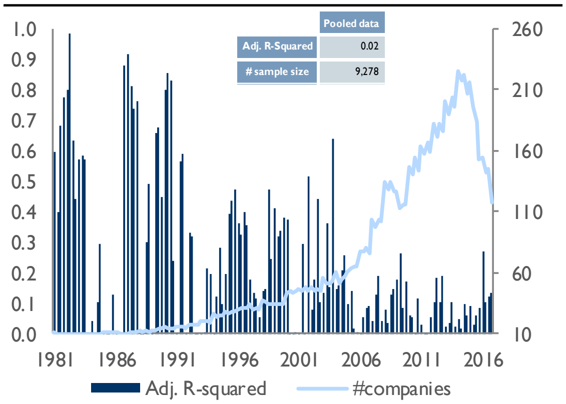

Source: Own creation

## ln EV/EBITDA regression

### *Model evaluation and summary statistics*

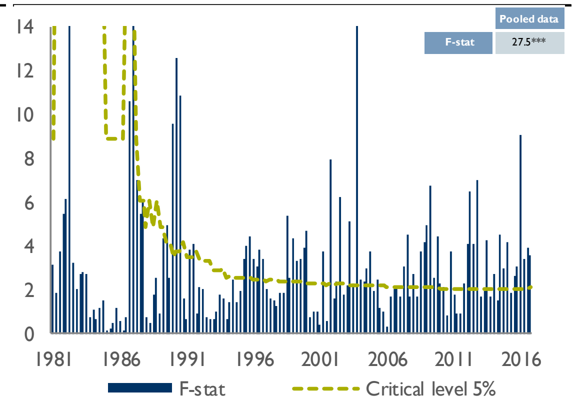
The ln EV/EBITDA multiple is regressed on ROIC, reinvestment rate, capital intensity, NOPAT growth, beta, profit margin risk and operating liability risk. The explanatory power of this model has evolved differently than in the ln P/B and ln P/E regressions. As seen in figure 9.2.13, the adjusted R-squared is not exhibiting the same steep downward trend as the previous models, but a more cyclical pattern is present. The median adjusted R-squared throughout the period is 0.13, better than the P/E regression and lower than the P/B regression, but the median standard error of the estimate at 0.79 is actually lower than both the previous regressions. The joint significance test in figure 9.2.14 depicts a fluctuating trend, with peaks and troughs throughout, indicating that the joint significance of the coefficients is shifting from significant to insignificant from period to period, and 62 out of 144 quarters are significant at a 95% confidence level.

**Figure 9.2.13 - Adjusted R-squared & sample size**




Source: Own creation

**Figure 9.2.14 - Joint significance test**




Source: Own creation

Like in the other models, all coefficients exhibit shifting sign over the period, evidently seen in the summary statistics in figure 9.2.15. The most frequently significant driver is the capital intensity with 41 significantly quarters, while the frequency is quite low for the other drivers. Profit margin risk is the only coefficient that is depicting the factual theoretically sign of the median coefficients, while ROIC, capital intensity and operating liability risk are opposite to what is suggested by theory. The remaining coefficients are more or less equal to zero. Furthermore, there are considerably more multicollinarity between the variables in this model than the other ones, clearly seen by an increased quantity of quarters where the VIF exceeds the threshold level of 10. ROIC, for instance, exhibits collinearity in 34 out of 144 quarters, which is important to bear in mind when looking at the trend in this coefficient.

The pooled data regression with 9,278 observations has a low adjusted R-squared, but the independent variables are jointly significant. Moreover, ROIC is statistically significant and negative, and capital intensity is significantly positive, which is opposite to what was predicted by the theory, but partly matching the relationship uncovered in the industry analysis. Lastly, the profit margin takes on the "correct" sign and is statistically significant.

**Figure 9.2.15 - Summary statistics ln EV/EBITDA regression**

**Quarterly data**

| Adjusted R-squared | | | R-squared | CI† |
|---|---|---|---|---|
| Min. | Median | Max. | Median | #/total |
| -1.58 | 0.13 | 0.98 | 0.35 | 45/144 |

| Std. Error of Estimate | | | F-test | |
|---|---|---|---|---|
| Min. | Median | Max. | Median | # sig./total |
| 0.11 | 0.79 | 2.37 | 2,41 | 0/144 |

| | Min. | Median | Max. | # sig./total | # VIF‡/total |
|---|---|---|---|---|---|
| Intercept | -1.68 | 2.07 | 16.76 | 0/144 | n.a. |
| ROIC | -48.54 | -0.16 | 12.29 | 0/144 | 35/144 |
| Reinvestment rate | -0.62 | 0.00 | 0.20 | 0/144 | 10/144 |
| Capital Intensity | -15.70 | 0.21 | 5.17 | 0/144 | 10/144 |
| NOPAT Growth | -1.19 | 0.00 | 2.19 | 0/144 | 17/144 |
| Beta | -1.91 | 0.00 | 2.92 | 0/144 | 1/144 |
| Profit margin risk | -12.14 | -0.26 | 4.96 | 0/144 | 10/144 |
| Operating liability risk | -3.87 | -0.05 | 2.99 | 0/144 | 24/144 |

# sig/.total: number of significant quarters of total (95% conf. level)

†: number of quarters with moderate to strong multicollinarity/value of condition index. Strong to moderate multicollinarity when 100<CI<1000

‡: quarters (#) with multicollinarity/variable is highly multicollinare when VIF>10

**Pooled data**

| # sample size | Adj. R-squared | F-test | Std.Error | CI† |
|---|---|---|---|---|
| 9,278 | 0.0196 | 27,5*** | 1.83 | 27.98 |

| | Coef. | VIF‡ |
|---|---|---|
| Intercept | 2,37*** | n.a. |
| ROIC | -0,005* | 1.16 |
| Reinvestment rate | -0.0000 | 1.00 |
| Capital Intensity | 0,03*** | 1.00 |
| NOPAT Growth | -1,44 | 1.00 |
| Beta | 0,0076 | 1.00 |
| Profit margin risk | -0,13* | 1.16 |
| Operating liability risk | -0,0005 | 4.25 |

*Significant at 90 % confidence level.

**Significant at 95 % confidence level.

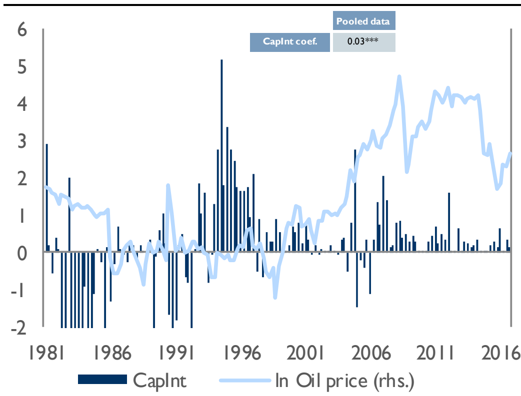
***Significant at 99 % confidence level.

Source: Own Creation

### *Analysis of selected regression coefficient over time*

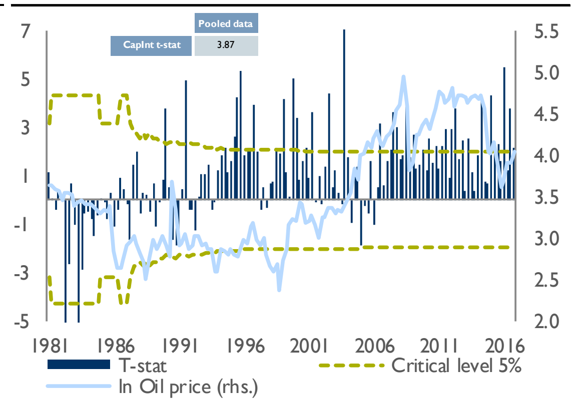
The capital intensity coefficient was the most frequent significant driver of multiple, but the sign was opposite of what was suggested by theory. Figure 9.2.16 visualises the fluctuating evolvement in the capital intensity coefficients. After 1994, however, the coefficients have mainly stayed positive, after a period with a highly negative sign. Investors are thus applying higher multiples for companies with higher capital intensity. The industry analysis noticed that the negative relationship seemed to hold between 2001 and 2004, but figure 9.2.17 does not confirm this relation. The magnitude of the coefficient decreases in that period, but it never turns negative and we fail to reject the null hypothesis that the coefficient is different from zero. Another point to be made is that the coefficient is statistically different from zero much more while positive than negative, further strengthening the positive sign of the coefficient in the pooled data regression. This may signal that investors place value on the outlook of more oil and revenue in the future, due to the fact the capital intensity increases when oil companies invest in more oil reserves and increased oil production.

**Figure 9.2.16 - Capital intensity coef. & Oil price**




Source: Own creation

**Figure 9.2.17 - Capital intensity t-stat & Oil price**

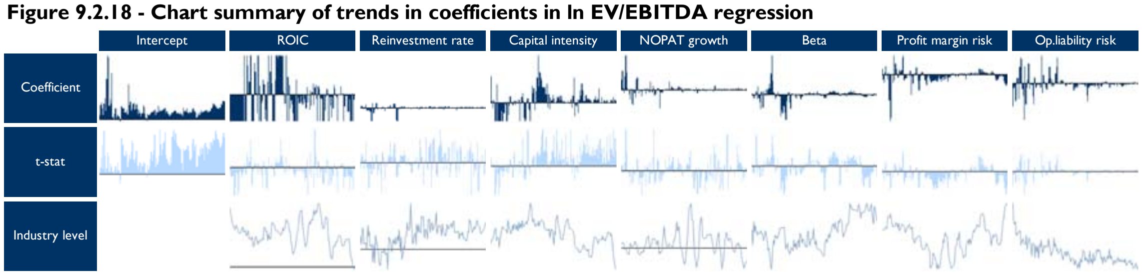



Source: Own creation

*Trend summary of all regression coefficients*

Although the ROIC coefficient has been highly fluctuating, it has been mostly negative the last 10 years, while appearing economically significant. However, the variable is rarely able to pass the test of statistical significance. The reinvestment rate, on the other hands, is not only statistical insignificant, but it also looks insignificant from an economic point of view as well. Moreover, the 1-year NOPAT growth has fluctuated a lot, loosing much of its economic significance and rarely statistical significant. The same is true for beta as well, but the beta has been negative the last seven years with some quarters of statistical significance. On the opposite side is the profit margin risk, which has been able to retain its economic significance over the period, while staying negative and statistically significant in every quarter of 2016, indicating that investors now are focusing more on operational efficiency. Lastly, the operating liability risk is volatile, but mostly negative, and over the last 20 years the coefficient has been deteriorating, reducing its economic significance. See appendix 9.2 for detailed graphs.

**Figure 9.2.18 - Chart summary of trends in coefficients in ln EV/EBITDA regression**




Source: Own creation

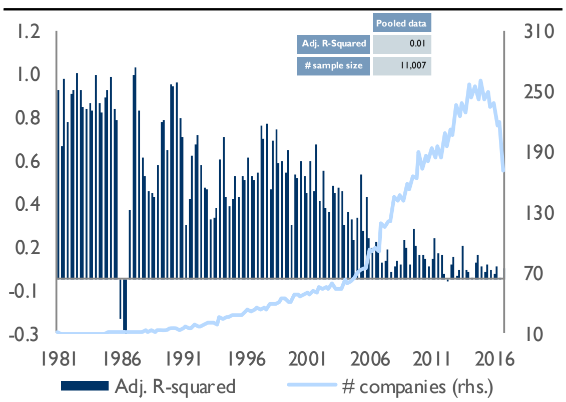
## ln EV/Sales regression

*Model evaluation and summary statistics*

The ln EV/Sales multiple is regressed on ROIC, NOPAT-margin, FCFF-margin, NOPAT growth, beta and operating liability risk. This model has the highest median adjusted R-squared (0.40) of all the models, and figure 9.2.19 shows that it has been much higher than the others over a longer horizon. However, there are three negative quarters that catches the eye immediately. The model seems to be very poor at fitting data in 1986. As described in the industry analysis, the oil price tanked in 1986, and this crash seems to be a plausible explanation for the negative R-squared that year. These coinciding events made us investigate the relationship between the oil price and the adjusted R-squared closer. After performing a recursive regression of the adjusted R-squared on the ln oil price, it confirms that there exists a statistically significant positive relationship between the oil price and the adjusted R-squared from 1986 until the last quarter of 2005. From there on forward, the relationship turns, and becomes statistically negative in early 2008, establishing a negative relationship between the explanatory power of the model and the oil price. See appendix 9.2.1 for a graphical illustration.

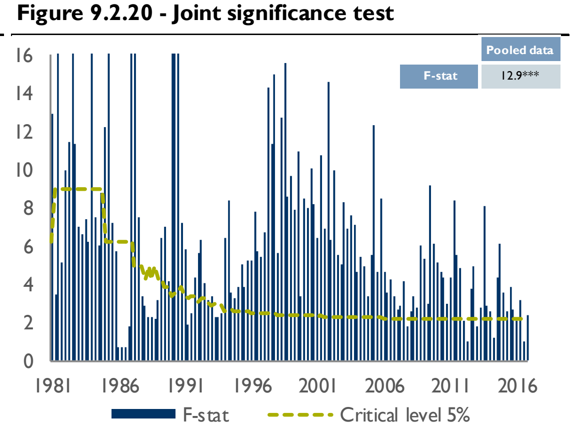
The joint significance test paints a robust picture of the model. Out of 144 quarters, 112 is significant, which indicates that the coefficients are jointly significantly different from zero most of the time. With the trivial R-squared in 1986 in mind, it is not surprising that the model fails the joint significance test in 1986 as well. After the oil price fall in 1986, there are three more periods where the model is, according to the test, not joint significant, but then the model is quite consistent above the critical level the rest of the period.

**Figure 9.2.19 - Adjusted R-squared & sample size**




Source: Own creation

**Figure 9.2.20 - Joint significance test**




Source: Own creation

All the median coefficients, except the NOPAT-margin and beta, in the summary statistics table in figure 9.2.21 takes on the opposite sign of the one anticipated by the valuation theory. The most frequent significant drivers are the FCFF-margin and the NOPAT-margin, with respectively 46 and 38 significant quarters.

**Figure 9.2.21 - Summary statistics ln EV/Sales regression**

**Quarterly data**

| Adjusted R-squared | | | R-squared | CI† |
|---|---|---|---|---|
| Min. | Median | Max. | Median | # |
| -0.26 | 0.40 | 0.98 | 0.53 | 29/144 |

| Std. Error of Estimate | | | F-test | |
|---|---|---|---|---|
| Min. | Median | Max. | Median | # sig./total |
| 0.20 | 1.09 | 2.65 | 5,40 | 0/144 |

| Variable | Min. | Median | Max. | # sig./total | # VIF‡/total |
|---|---|---|---|---|---|
| Intercept | -2.40 | 0.60 | 1.96 | 0/144 | n.a. |
| ROIC | -22.65 | -0.05 | 16.03 | 0/144 | 32/144 |
| NOPAT margin | -13.01 | 0.73 | 31.22 | 0/144 | 24/144 |
| FCF margin | -3.64 | -0.30 | 5.22 | 0/144 | 24/144 |
| NOPAT growth | -5.49 | -0.00 | 1.58 | 0/144 | 16/144 |
| Beta | -1.91 | -0.02 | 1.32 | 0/144 | 0/144 |
| Operating liab. risk | -4.56 | -0.64 | 1.11 | 0/144 | 20/144 |

# sig/.total: number of significant quarters of total (95% conf. level)

†: number of quarters with moderate to strong multicollinarity/value of condition index. Strong to moderate multicollinarity when 100<CI<1000

‡: quarters (#) with multicollinarity/variable is highly multicollinare when VIF>10

**Pooled data**

| # sample size | Adj. R-squared | F-test | Std.Error | CI† |
|---|---|---|---|---|
| 11,007 | 0.0065 | 12,9*** | 2.31 | 25.81 |

| Variable | Coef. | VIF‡ |
|---|---|---|
| Intercept | 1,05*** | 1.04 |
| ROIC | -0,008** | 1.04 |
| NOPAT margin | -0,003*** | 1.02 |
| FCF margin | -1,059 | 1.02 |
| NOPAT growth | -0,00006 | 1.00 |
| Beta | 0,0012 | 1.00 |
| Operating liab. risk | -0,003*** | 1.04 |

*Significant at 90 % confidence level.

**Significant at 95 % confidence level.

***Significant at 99 % confidence level.

Source: Own Creation

The pooled regression model suggests that there is a statistically significant negative relationship between the EV/Sales multiple and ROIC, NOPAT-margin and operating liability risk. It is hard to explain why this should be the case, especially the negative sign on ROIC and NOPAT-margin. One explanation for the sign of the ROIC coefficient may be that decreasing sales eventually reduce ROIC, and if we assume that investors are pricing E&P companies on mid-cycle oil prices or normalised operating income, then we will see an increase in the multiple at the same time as ROIC is falling.

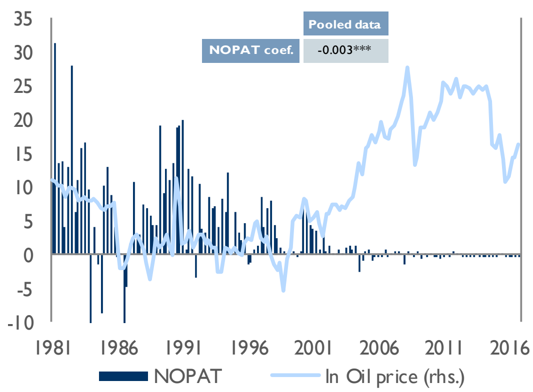
### *Analysis of selected regression coefficient over time*

Investors have rewarded E&P companies with higher NOPAT-margins a higher EV/Sales multiple for the first two decades of the sample period, as seen by the positive coefficient in figure 9.2.22. The magnitude of the coefficient is also noticeable large, which means that the economically significance of the NOPAT-margin has been prevalent the first two decades. Coupled with statistical significance matching most of the peaks in the coefficient (see appendix 9.2.1), the first two decades reveals the prominence of the NOPAT-margin for the multiple. The coefficient and the oil price seems to follow each other fairly well the same period, indicating that investors are rewarding companies more for higher margins when the oil price is rising and opposite when it is falling. One could easily argue that an increase in the oil price, would make the oil companies' operations much more profitable, thus increasing the NOPAT-margin.

This could also be explained by the fact that the NOPAT-margin most likely increases as oil companies are able to run more profitable operations as the oil price rises.

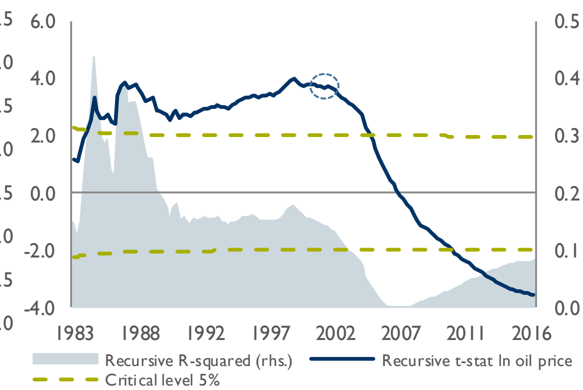
As we have seen in some of the other models, the early 2000s marks a turning point for the fundamentals' impact on multiples. The coefficient is clearly losing much of its economically significance at this point in time, while frequency of negative coefficients increases (see appendix 9.2.1). Due to the long-lived rise in the oil price that sparked off at that point, we have done a recursive regression of the NOPAT-margin coefficients on the ln oil price over the entire period to see if the oil price may have an explanatory impact.

**Figure 9.2.22 - NOPAT margin coef. & Oil price**




Source: Own creation

**Figure 9.2.23 - Reg. NOPAT coef. on ln Oil price**



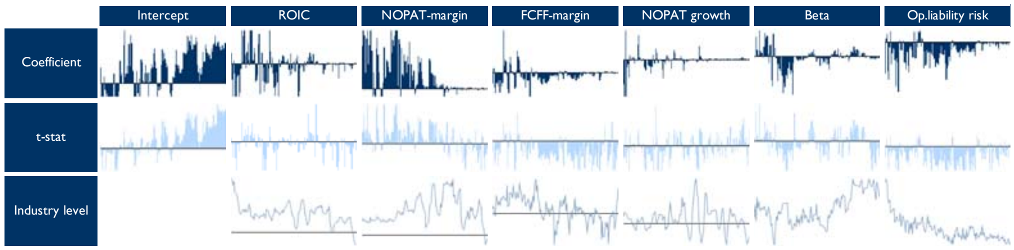

Source: Own creation

Figure 9.2.23 confirms the positive relationship between the oil price and how much investors reward companies for higher margins the first two decades. The turning point in early 2000s is clearly seen as the beginning of a downward trend in the t-stat, indicating that the positive effect from the oil price on the NOPAT coefficient is tapering off. The t-stat breaks the critical level in 2011 and stays statistically significant negative from that time on, telling us that rising oil prices now have a negative impact on the magnitude of the NOPAT coefficient. As a result, the oil price seems to have an explanatory power on the fall in the NOPAT margin coefficient, but the R-squared reveals that there are other things in play as well.

*Trend summary of all regression coefficients*

Figure 9.2.24 summarises the results from the quarterly regressions. Interestingly, the FCFF-margin is almost consistently negative over the period. Increased cash flow margins thus have a negative impact on the multiple, which does not immediately make sense. However, a common way of increasing the cash flow is to reduce investments, and investors may punish companies for focusing more on short term cash generation than the long-term cash flow potential. ROIC has shifted from positive to negative numerous times throughout the period, but it has only been statistically significant positive in two quarters. Similarly, beta has been fluctuating a lot, but its statistically significance is not impressive. Nevertheless, the coefficient shifted from positive to negative after the oil price crash in 2014, and it has been statistically significant in some of the periods in the aftermath. Lastly, the operating liability risk has been consistently negative, opposite to what was predicted by the theory. Still, the operating liability risk coefficient has shown quite a meaningful impact, underpinning the economic significance.

**Figure 9.2.24 - Chart summary of trends in coefficients in ln EV/Sales regression**

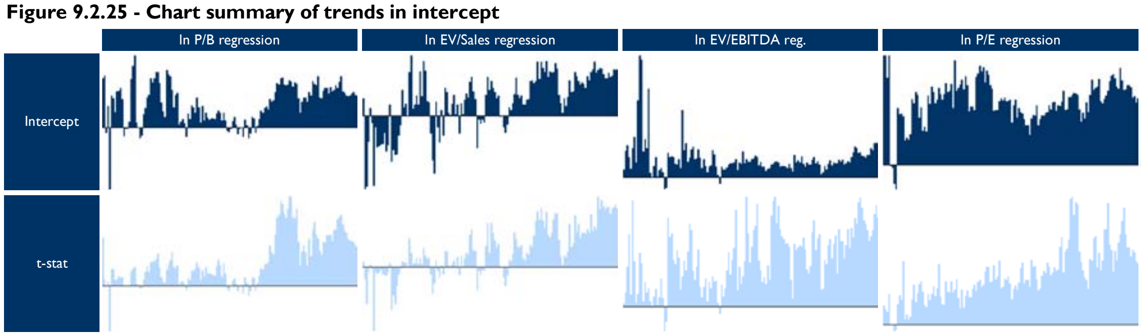



Source: Own creation

## Intercept discussion

After looking at all the chart summaries of the coefficients in the previous sections, there are a common feature that stands out. Most of the coefficients, with some exceptions, are depicting a decreasing trend, where they get less and less economically significantly. Contrary, the intercept shows the opposite trend in both the ln P/B and the ln EV/Sales regression, where the magnitude of the intercept appears to increase at the same point in time where many of the coefficients are losing its economically relevance. This trend is however not prevalent when eyeballing the intercepts of the ln EV/EBITDA and ln P/E regressions, which are multiples with a much more unstable denominator. All the intercepts and corresponding trends in t-stats are illustrated in figure 9.2.25.

**Figure 9.2.25 - Chart summary of trends in intercept**




Source: Own creation

The intercept is where the regression line crosses the y-axis, and it crosses the y-axis where the mean of the residuals is zero, thus the constant is adjusting itself to what works mathematically to produce the zero mean. The intercept is the mean response when all the independent variables are set to zero, which is often impossible, and there seem to be a general perception that the value of the intercept is almost always meaningless. However, the constant term is also said to be the garbage collector of the regression model because it serves as a garbage bin for any bias that is not accounted for in the model (Frost, 2013). Thus, at the risk of stepping into a minefield, we will try to interpret how this "garbage collector" have behaved in terms of its own trend across time.

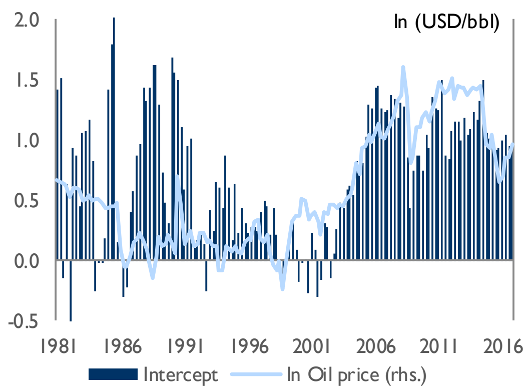
Abrams (2012) writes that the significance of the intercept is irrelevant in regressions of an absolute dependent variable, because it does not make-or-break the regression if the true value of the intercept might be zero. But when working with scaled dependent variables, he claims, that the significance of the intercept matters. He argues that if all the value drivers are insignificant and the intercept is significant, it means that the average multiple of the observations is likely to be a valid forecast of value, since we can reject the null hypothesis that the multiple equals zero.

To begin with, let us think about how the intercept may increase or decrease. If the market assigns higher multiples to a sector without any changes in the underlying fundamentals, it means that the intercept will be pushed up compared to the previous regression line. The intercept is thus picking up some new effects that the model is missing. Opposite, if the multiples decrease without any change in the fundamentals, the intercept will decrease. Similarly, if the fundamentals are deteriorating (increasing) and the multiples stay flat, the intercept will increase (decrease). Following this thought process, it may be fair to assume that the intercept is catching market behaviour beyond our model.

Another point to be made is that the mean industry multiple and the intercept will probably be close to each other when the regression model has a low R-squared. To drive this argument home, we must think about what the R-squared is measuring. It measures the spray between the fitted responses and the observed responses, and a larger variance yields lower R-squared and a flat regression line is not surprising in such an environment. A regression line can be flat if the intercept is significant and the independent variables are economically and statistically insignificant. Consequently, the flat regression line, mainly represented by the intercept, will almost be equivalent to the mean multiple in the industry.

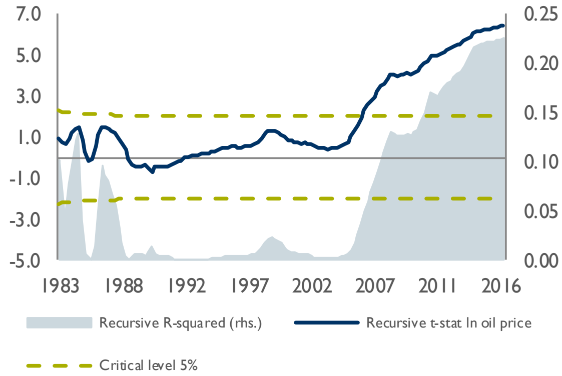
This train of thought is unfolding itself into two hypothesizes. First, the intercept in the ln P/B model increases in 2003/2004 because it picks up an higher oil price which is not accounted for in the model. Figure 9.2.27 reveals that the intercept follows the oil price closely from the oil price hike in 2003/2004. However, to determine if the oil price actually has a statistically significant effect on the intercept, we performed a recursive regression of the intercept on the ln oil price. As seen in figure, 9.2.29, the oil price t-stat shifts in 2003/2004 and the explanatory power of the oil price on the intercepts increases dramatically. Not long after, the relationship also turns significantly positive, indicating that a higher oil price leads to a higher intercept. Looking back, with today's glasses, at the development of the intercept, the R-squared tells us that over 20% of the historical variation can be explained by the oil price.

**Figure 9.2.27 - Intercept ln P/B & ln Oil price**




Source: Own creation

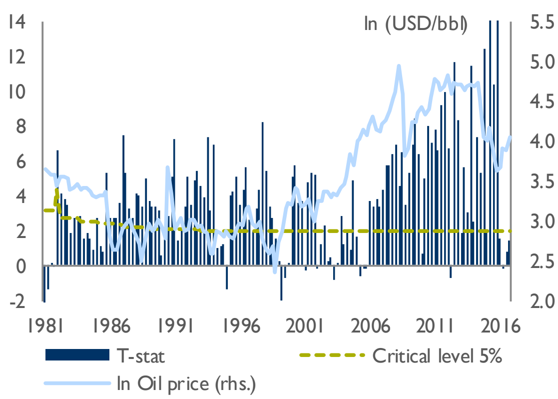
**Figure 9.2.28 - Reg. intercept (ln P/B) on ln Oil price**




Source: Own creation

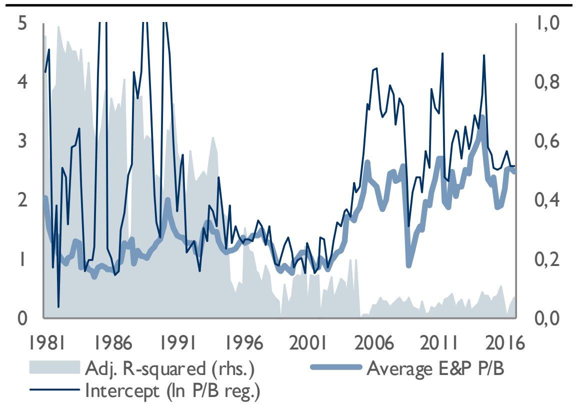
The second hypothesis that comes to mind is that the difference between the intercept and the average sector P/B multiple has decreased in line with a lower adjusted R-squared from the model, an hypothesis backed by figure 9.2.30. The difference between the intercept and the average P/B multiple narrows when the adjusted R-squared decreases and widens when it increases.

**Figure 9.2.29 - T-stat intercept & ln Oil price**




Source: Own creation

**Figure 9.2.30 - Intercept vs. avg. P/B & R-squared**




Source: Own creation

Interestingly or maybe naturally, they follow each other particularly close from 1995 until 2006, exactly the same period where figure 8.2.3 in the industry analysis showed a close relationship between the oil price and the median P/B multiple in the industry. This further strengthens the observations suggesting that investors are weighting the higher oil price more than decreasing fundamentals when they evaluate the companies in that period of time, which is captured by the intercept and falling coefficients. A quick simple regression of the difference between the intercept and the average multiple on the adjusted R-squared, confirms the positive relation between the difference and the adjusted R-squared (see appendix 9.2.2 for regression results).

Similar observations can be seen in the ln EV/Sales multiple as well, but the relationship between the intercept and the oil price is first significantly negative before it turns significantly positive at about the same time as it did in figure 9.2.28. The explanatory power of the oil price is also higher in the beginning before it drops and then turns upwards again when the oil price is surging.

### Conclusive thoughts and hypotheses assessment

The theoretical multiple drivers are undoubtedly unstable in terms of economical and statistical significance. Moreover, their coefficients are changing erratically and fluctuates from positive to negative territory in just a few quarters, and the drivers that are most significant in terms of frequency are often not the same that are significant in the pooled model. This makes it difficult to assign only one conclusion to how certain drivers affect a multiple over time, but some features have materialised itself throughout the analysis. Firstly, there is a general observation that the statistically significantly drivers in both the quarterly and pooled regressions exhibits a low degree of economically significance, evidently seen by the moderate magnitude of the coefficients. The NOPAT-margin is one of few exceptions with a high coefficient over a longer period of time.

Secondly, coefficients are not always depicting the sign expected by theory and some take on a different signa dependent on what multiple the driver is applied on. For instance, ROE is statistically significantly negative in the P/E regression, but positive in most of the quarters in the P/B regression. This corresponds to the observations in the industry analysis, and suggest that the volatile P/E multiple is similar to the illustrative cyclical multiple in figure 5.4.3 which is inversely related to the cycle. Similarly, both the ROIC and the NOPAT-margin is statistically significantly negative when doing pooled regressions on the EV/EBITDA and EV/Sales multiples, but their economically significance is low.

Lastly and perhaps most interestingly, there is a fascinating pattern evolving in the quarterly P/B and EV/Sales regressions. According to our regressions, the magnitude of almost all the coefficients in these regressions are diminishing at the same point in time, while the intercept is increasing. This trend starts in the early 2000s when the oil price is seriously starts to rise and the fundamentals slowly are beginning to deteriorate. Both of the two most frequently significant drivers in the P/B and EV/Sales regressions illustrated this development, and it was found that the oil price had a statistically significant impact on the coefficients on the downside corresponding to the point in time where the coefficients started to stumble. Figure 8.2.3 and 8.2.4 in the industry analysis disclosed rising multiples in the same period, which means that the multiples are increasing at the same time as the fundamentals are decaying. However, figure 8.2.1 and appendix 8.2 revealed that the median market value/enterprise value in the industry followed the oil price particularly close from the early 2000s and other figures showed that the market value/enterprise value growth detached from the book value/sales growth after the oil crisis in 1997 before it shifted gear in early

2000s and grew much faster than the value driver. This fuels the hypothesis that investors to a larger extent have ignored fundamentals the last two decades and only cared about the oil price. The coinciding uptick in the "garbage collector" is assumed to capture the higher oil price environment, and the oil price is therefore a factor to consider when explaining why the intercept is more economically significant than the apparent theoretically drivers.

Due to the great number of hypotheses, answers to all the hypotheses formulated in the previous sections regarding the E&P sector are summarised in figure 9.2.31 below:

**Figure 9.2.31 - Assessment of E&P hypotheses**

| | | | ROE | ROIC | NOPAT-margin | Growth | Capital intensity | Reinvestment rate | FCFF-margin | Beta | Profit margin risk | Op.liability risk | Debt to equity | Oil price |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **P/B** | Overall | Hypothesis: | pos. | | | pos. | | | | pos/neg. | neg. | unclear. | pos/neg. | pos. |
| | Quarterly | Mostly pos/neg? | pos. | | | pos/neg. | | | | pos/neg. | pos/neg. | pos/neg. | pos/neg. | |
| | | Mostly statistically significant? | ✓ | | | × | | | | × | × | × | × | |
| | | Economically significant? | < 2001 | | | < 1993 | | | | < 1991 | < 2000 | < 2000 | < 1996 | |
| | Pooled | Positive or negative? | pos. | | | neg. | | | | neg. | pos. | neg. | pos. | pos. |
| | | Statistically significant? | × | | | × | | | | ✓ | × | × | × | ✓ |
| | | Economically significant? | × | | | × | | | | × | × | × | × | ✓ |
| **P/E** | Overall | Hypothesis: | neg. | | | neg. | | | | pos/neg. | pos/neg. | unclear | pos/neg. | pos. |
| | Quarterly | Mostly pos/neg? | neg. | | | neg. | | | | pos/neg. | pos/neg. | pos/neg. | pos/neg. | |
| | | Mostly statistically significant? | × | | | × | | | | × | × | × | × | |
| | | Economically significant? | < 2001 | | | < 2001 | | | | ✓ | < 2006 | < 2001 | < 1987 | |
| | Pooled | Positive or negative? | neg. | | | pos. | | | | neg. | pos. | neg. | pos. | pos. |
| | | Statistically significant? | ✓ | | | × | | | | × | ✓ | ✓ | × | ✓ |
| | | Economically significant? | × | | | × | | | | × | × | × | × | ✓ |
| **EV/EBITDA** | Overall | Hypothesis: | | neg. | | neg. | pos/neg. | neg. | | pos/neg. | pos/neg. | unclear | | pos/neg. |
| | Quarterly | Mostly pos/neg? | | neg. | | pos/neg. | pos/neg. | pos/neg. | | pos/neg. | pos/neg. | pos/neg. | | |
| | | Mostly statistically significant? | | × | | × | × | × | | × | × | × | | |
| | | Economically significant? | | < 1985 | | < 2006 | ✓ | < 1992 | | < 1992 | < 2001 | < 1996 | | |
| | Pooled | Positive or negative? | | neg. | | neg. | pos. | neg. | | pos. | neg. | neg. | | pos. |
| | | Statistically significant? | | ✓ | | × | ✓ | × | | × | ✓ | × | | ✓ |
| | | Economically significant? | | × | | ✓ | × | × | | × | × | × | | ✓ |
| **EV/Sales** | Overall | Hypothesis: | | pos/neg. | pos. | pos/neg. | | | pos/neg. | pos/neg. | | unclear | | pos. |
| | Quarterly | Mostly pos/neg? | | pos/neg. | pos. | pos/neg. | | | neg. | pos/neg. | | neg. | | |
| | | Mostly statistically significant? | | × | × [1] | × | | | × | × | | × [2] | | |
| | | Economically significant? | | < 1995 | < 2001 | < 2002 | | | < 2005 | ✓ | | < 2007 | | |
| | Pooled | Positive or negative? | | neg. | neg. | neg. | | | neg. | pos. | | neg. | | pos. |
| | | Statistically significant? | | ✓ | ✓ | × | | | × | × | | ✓ | | ✓ |
| | | Economically significant? | | × | × | × | | | ✓ | × | | × | | ✓ |

Pos/neg: indicates that the relationship shifts from period to period     Mostly statistically significant: ✓=most of the quarters are significant, ×=seldom significant

Economically significant: < 2001 indicates that the coefficient has been signficiant until 2001, [2001;2005] = economcially significantly between 2000 and 2005, ✓=significant in most of the quarters, ×=seldom/never significant

[1] NOPAT margin is frequently statistically significant until 2001 [2] Op.liability risk is significant in 56/144 quarters

Source: Own creation

## 9.2.2 DRY BULK

In order to understand the relationship between the multiples in the dry bulk sector and the selected fundamentals, we have performed quarterly cross-sectional regressions each quarter from 2006 until the last quarter of 2016 and pooled cross-sectional regressions over the entire period. The analysed period is shorter than in the industry analysis since it is a critera that each sample company has a complete data set on the relevant variables for the regressions. Therefore, bear in mind that our starting point is in the aftermath of the down cycle in freight rates in 2006, which leads to the upturn that caused record high freight rates in 2008. It should also be noted that the sample size is much smaller than in the E&P section, and this may have an impact on the results from the quarterly regressions.

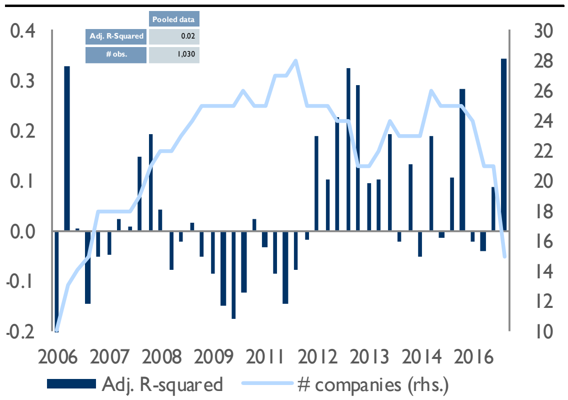
## ln P/B regression

### *Model evaluation and summary statistics*

The ln P/B multiple is regressed on ROE, book value growth, beta, profit margin risk, operating liability risk and debt-to-equity. The explanatory power of the model increases at the same time as the freight rates skyrockets, and collapses with the downturn in the freight rates in the fourth quarter of 2008. This marks the beginning of a 4-year period where the model is extremely bad at explaining the variations of the dependent variable, even though the rates pick up some lost ground over the period. The quarterly adjusted R-squared have fluctuated from negative to positive, but from 2012 it has increased and stayed more consistently positive, as seen in figure 9.2.31. The median adjusted R-squared over the entire period is 0.01, while the pooled regression with 1,080 observations yields a ratio of 0.02. In combination with a relatively high median standard error of 1.45, it indicates that the model predicts with a high uncertainty.

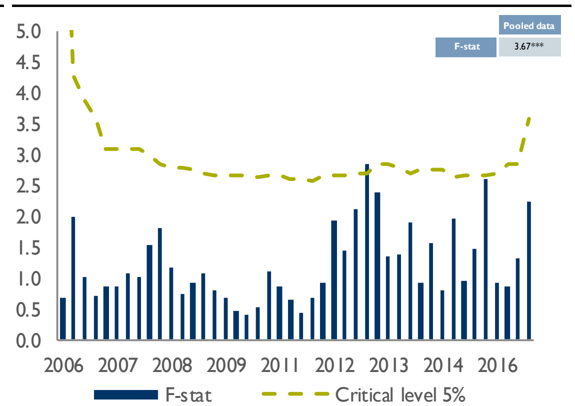
The quarterly F-stats from the regressions do not paint a rosy picture of the model either. As seen in figure 9.2.32, the coefficients in the model are only joint significant in one out of 44 quarters, implying that we cannot reject the null hypothesis that the coefficients together are not significant in explaining the variation in the multiple and the model is thus not better than the intercept-only model. However, the F-stat for the pooled regression model pass the significance test at a 99% confidence level.

**Figure 9.2.31 - Adjusted R-squared & sample size**




Source: Own creation

**Figure 9.2.32 - Joint significance test**




Source: Own creation

Like in the E&P sector, the coefficients have all shifted signs at least once throughout the period, easily seen by the negative minimum value and positive maximum value in figure 9.2.33. The relationship between the drivers and multiples is therefore not stable. Looking at the coefficients in terms of their significance frequency is not gloomy reading, where ROE is the most frequent significant driver with only 7 significant quarters out of 44.

**Figure 9.2.33 - Summary statistics In P/B regression**

**Quarterly data**

| Adjusted R-squared | | | R-squared | CI† |
|---|---|---|---|---|
| Min. | Median | Max. | Median | #/total |
| -0.27 | 0.01 | 0.34 | 0.32 | 22/44 |

| Std. Error of Estimate | | | F-test | |
|---|---|---|---|---|
| Min. | Median | Max. | Median | # sig./total |
| 0.43 | 1.45 | 2.04 | 1.02 | 1/44 |

| Variable | Min. | Median | Max. | # sig./total | # VIF‡/total |
|---|---|---|---|---|---|
| Intercept | -2.48 | -0.15 | 1.77 | 0/44 | n.a. |
| ROE | -5.24 | 1.28 | 9.40 | 6/44 | 7/44 |
| Book value growth | -13.45 | -0.43 | 19.19 | 4/44 | 2/44 |
| Beta | -1.15 | -0.10 | 0.32 | 6/44 | 0/44 |
| Profit margin risk | -1.55 | 0.75 | 4.13 | 1/44 | 0/44 |
| Operating liability risk | -3.39 | -0.54 | 2.60 | 1/44 | 3/44 |
| Debt to equity | -0.58 | 0.01 | 0.75 | 0/44 | 3/44 |

# sig/.total: number of significant quarters of total (95% conf. level)

†: number of quarters with moderate to strong multicollinarity/value of condition index. Strong to moderate multicollinarity when 100<CI<1000

‡: quarters (#) with multicollinarity/variable is highly multicollinare when VIF>10

**Pooled data**

| # sample size | Adj. R-squared | F-test | Std.Error | CI† |
|---|---|---|---|---|
| 1,030 | 0.02 | 3.67*** | 1.48 | 30.90 |

| Intercept | | ROE | | Book value growth | | Beta | | Profit margin risk | |
|---|---|---|---|---|---|---|---|---|---|
| Coef. | VIF‡ | Coef. | VIF‡ | Coef. | VIF‡ | Coef. | # VIF‡ | Coef. | VIF‡ |
| 0.46*** | n.a | -0.002 | 1.20 | 0.056 | 1.01 | -0.06*** | 1.01 | -0.23* | 1.01 |

| Operating liab. risk | | Debt to equity | |
|---|---|---|---|
| Coef. | VIF‡ | Coef. | VIF‡ |
| -0.001 | 1.18 | 0.05* | 1.01 |

*Significant at 90 % confidence level.

**Significant at 95 % confidence level.

***Significant at 99 % confidence level.

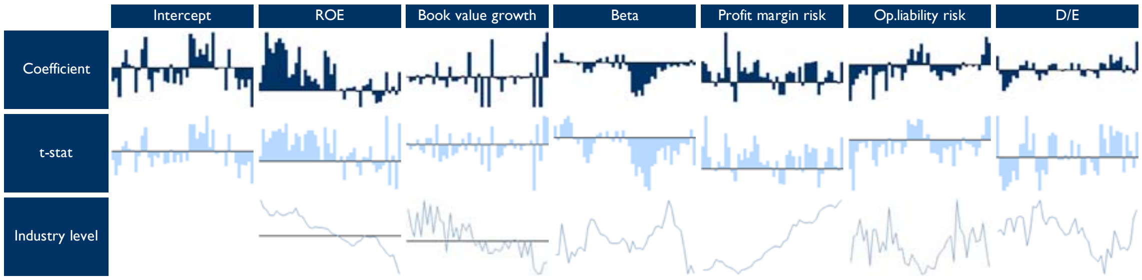
Source: Own Creation

Beta is strongly significant in the pooled model, while profit margin risk and debt-to-equity are weakly significant. Both beta and profit margin risk take on the expected sign, demonstrating the existence of a negative relationship between the multiple, the asset model pricing risk and the profit margin risk overall. The debt-to-equity ratio has a positive sign, which is contradictory to the risk theory section, but it is not that strange. If the financial leverage is favourable, i.e. the spread between returns and cost of borrowing, the P/B multiple will be inflated, and the positive sign may imply that investors reward companies that exploit favourable leverage.

*Trend summary of regression coefficients*

The ROE coefficient is positive and economical significant in terms of magnitude the first six years of the investigation period, but only statistically significant in five of the quarters. Its impact on the multiple has decreased the last six years at the same time as the industry ROE has plummeted, while the statistical significance has been almost completely absent. The book value growth fluctuates with sporadical significance, but it is worth to mention that it has been positive, and statistical and economical significant for the last two quarters of 2016. Moreover, beta has been consistently negative the last seven years with five statistically significantly quarters in 2012/2013, but the coefficient has witnessed an declining trend since the peak in 2013. The profit margin risk and operating liability are virtually never statistically significant, and the former one has been mainly positive whereas the latter one has been more fluctuating over the period. Lastly, debt-to-equity has swivelled from negative to positive territory throughout, but has never been statistical significant. See appendix 9.2.3. for detailed graphs.

**Figure 9.2.34 - Chart summary of trends in coefficients in ln P/B regression**



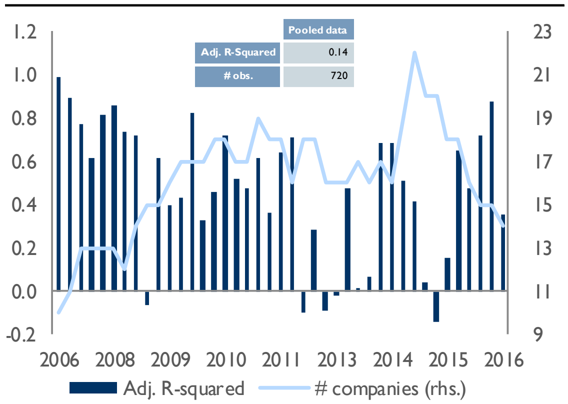

Source: Own creation

## ln EV/Sales regression

### *Model evaluation and summary statistics*

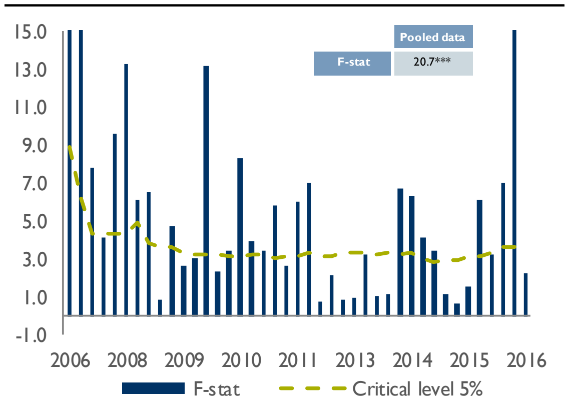
The ln EV/Sales multiple is regressed on ROIC, EBIT-margin, FCFF-margin, reinvestment rate, EBIT growth and beta. Figure 9.2.35 shows that this model has a higher and more stable adjusted R-squared than the ln P/B model, and is correspondingly more frequently significant when looking at the joint significance test in figure 9.2.36. In the aftermath of the financial crisis and the collapse of the freight rates, the model loses all its explanatory power, but quickly rebounds in line with the following upward correction in the freight rates. The median adjusted R-squared over the period is 0.5 and the median standard error is much lower than in the ln P/B model, while the pooled adjusted R-squared stands at 0.14.

**Figure 9.2.35 - Adjusted R-squared & sample size**




Source: Own creation

**Figure 9.2.36 - Joint significance test**




Source: Own creation

The minimum and maximum values of the coefficients in figure 9.2.37 ranges from negative to positive values, indicating that investors have punished and rewarded companies for an increase in the fundamental drivers over the period. There is especially one driver that stands out from the crowd in the summary statistics, both in terms of economically and statistically significance. The median coefficient on the EBIT-margin is high and it is statistically significant in almost half of the quarters. The other quarterly coefficients do not depict the same robustness, except for the intercept which is statistically significant in 26 quarters.

Data from the pooled regression confirms the importance of the EBIT-margin on the multiple in terms of significance and directional relationship. The FCFF-margin, beta and intercept follow the EBIT-margin when it comes to significance. However, the FCFF-margin takes on a negative sign, which is opposite to what is expected, but in line with what was observed in the industry analysis. That said, it should be noted that the regressions are experiencing some multicollinarity, which should make us somewhat cautious when interpreting the coefficients.

**Figure 9.2.37 - Summary statistics In EV/Sales**

**Quarterly data**

| Adjusted R-squared | | | R-squared | CI† |
|---|---|---|---|---|
| Min. | Median | Max. | Median | #/total |
| -0.14 | 0.51 | 0.98 | 0.69 | 28/41 |

| Std. Error of Estimate | | | F-test | |
|---|---|---|---|---|
| Min. | Median | Max. | Median | # sig./total |
| 0.07 | 0.48 | 1.42 | 3.91 | 23/41 |

| | Min. | Median | Max. | # sig./total | # VIF‡/total |
|---|---|---|---|---|---|
| Intercept | -0.32 | 0.83 | 1.57 | 26/41 | n.a. |
| ROIC | -11.84 | -1.20 | 0.50 | 10/41 | 3/41 |
| EBIT margin | -0.68 | 2.27 | 4.96 | 20/41 | 0/41 |
| FCFF margin | -1.09 | -0.09 | 0.49 | 6/41 | 11/41 |
| Reinvestment Rate | -0.24 | -0.00 | 0.27 | 6/41 | 13/41 |
| EBIT growth | -3.17 | -0.08 | 2.60 | 8/41 | 5/41 |
| Beta | -0.23 | -0.01 | 0.36 | 1/41 | 0/41 |

# sig/.total: number of significant quarters of total (95% conf. level)

†: number of quarters with moderate to strong multicollinarity/value of condition index. Strong to moderate multicollinarity when 100<CI<1000

‡: quarters (#) with multicollinarity/variable is highly multicollinare when VIF>10

**Pooled data**

| # sample size | Adj. R-squared | F-test | Std.Error | CI† |
|---|---|---|---|---|
| 720 | 0.14 | 20.7*** | 0.84 | 399.54 |

| Intercept | | ROIC | | EBIT margin | | FCFF margin | | Reinvestment Rate | |
|---|---|---|---|---|---|---|---|---|---|
| Coef. | VIF‡ | Coef. | VIF‡ | Coef. | VIF‡ | Coef. | # VIF‡ | Coef. | VIF‡ |
| 1.17*** | n.a | -0.05 | 1.21 | 0.272** | 1.01 | -0.07*** | 1.20 | -0.0002 | 1.00 |

| EBIT growth | | Beta | |
|---|---|---|---|
| Coef. | VIF‡ | Coef. | VIF‡ |
| -0.0031 | 1.01 | -0.02* | 1.01 |

*Significant at 90 % confidence level.

**Significant at 95 % confidence level.

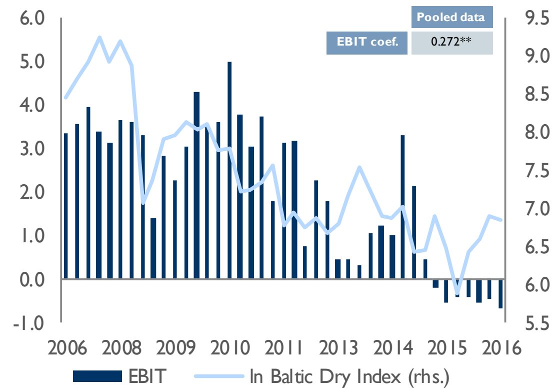
***Significant at 99 % confidence level.

Source: Own Creation

### *Analysis of selected regression coefficient over time*

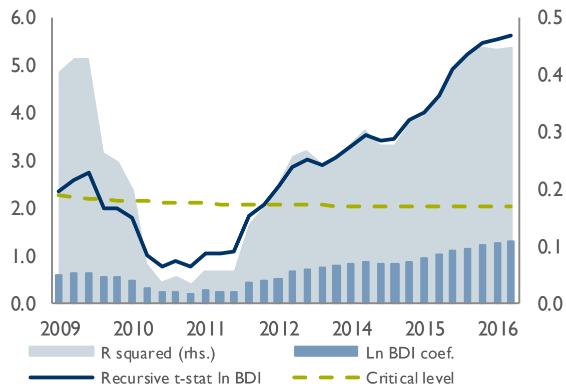
According to the results above, the EBIT-margin is a key driver of the EV/Sales multiple. Figure 9.2.38 displays the trend and level of the coefficient over the entire period, and we notice that the coefficient has been economically significant for a number of periods.

**Figure 9.2.38 - EBIT coef. on Baltic Dry Index**




Source: Own creation

**Figure 9.2.39 - Reg. EBIT coef. on Baltic Dry Index**




Source: Own creation

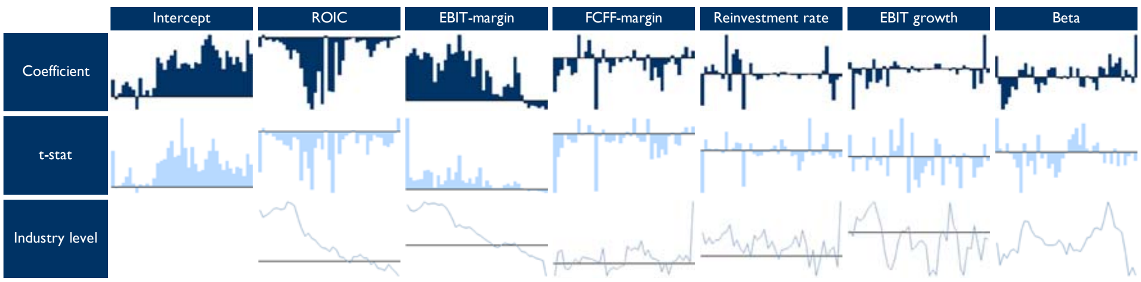
The coefficient is especially impactful on the multiple from the first quarter of 2006 until the first quarter of 2012, but then the magnitude of the coefficient nosedives. Since then, the coefficient has stumbled further down, except for a spike in 2014, and it has actually turned negative the last two years. Likewise, the statistical significance of the variable has deteriorated in the same period and the EBIT-margin has not been a statistically significant factor for the multiple the last six years (see appendix 9.2.3.1).

The Baltic Dry Index has been in an overall downward trend since its heights of 2007, and there seem to be a covariation between the magnitude of the coefficient on the EBIT-margin and the freight rate index, which may be an explanation of the reduced willingness to reward dry bulk companies with higher margins. To test for this hypothesis, we performed a number of regressions of the coefficients on the natural logarithm of the Baltic Dry Index, where we expanded the sample with observations one after another. Figure 9.2.39 summarises the results from the recursive regressions. There has been a positive relationship between the freight rate index and the coefficient over the entire period, but there are two periods of particular interest. After the peak in the freight rates in 2009, the relationship with the EBIT-margin coefficient turns less positive and it stays smaller than usual in a window of almost two years. During these years, the freight rate index has no statistically significant explanatory power on the magnitude of the coefficient. This period ends at the beginning of 2012, when the positive relationship picks up again and turns significantly more positive than before. This means that the downward trend in the freight rate index pushes the EBIT-margin coefficients considerably lower with both stronger statistical and economical force from that point in time. However, the R-squared indicates that there are other unidentified factors that affect the observed investor behaviour as well.

*Trend summary of regression coefficients*

ROIC is almost consistently negative over the entire period of time, but it is seldom statistical significant. The other coefficients display a much more erratic and vacillating development, and only occasionally significant with a lower economically impact on the multiple. See appendix 9.2.3 for detailed graphs.

**Figure 9.2.40 - Chart summary of trends in coefficients in ln EV/Sales regression**



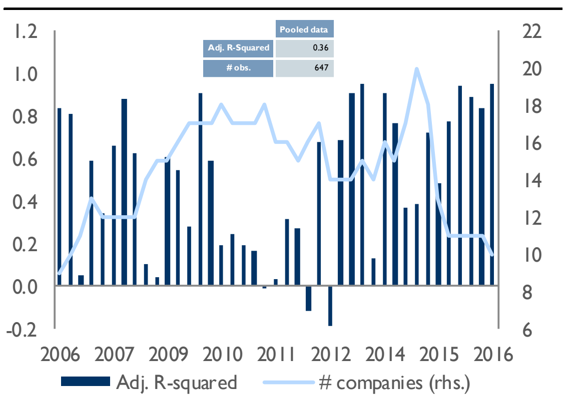

Source: Own creation

### 9.2.2.3 ln EV/EBITDA regression

*Model evaluation and summary statistics*

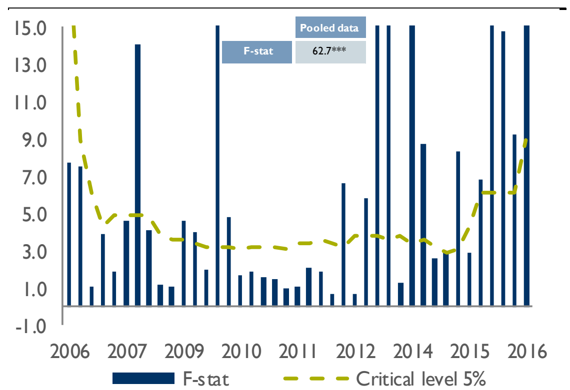
The ln EV/EBITDA multiple is regressed on ROIC, reinvestment rate, capital intensity, EBIT growth, beta and profit margin risk. The adjusted R-squared in figure 9.2.41 is volatile, but it is quite high in most of the quarters. Moreover, it has the highest median adjusted R-squared and pooled regression adjusted R-squared when comparing it to the other two models, with a ratio of 0.59 and 0.36 respectively. Similarly, it also has the lowest standard error of estimate and the joint significance test implies that the coefficients are jointly significantly different from zero 18 out of 41 quarters, indicating that the model performs better than the intercept-only model.

**Figure 9.2.41 - Adjusted R-squared & sample size**




Source: Own creation

**Figure 9.2.42 - Joint significance test**




Source: Own creation

The summary statistics from the regressions are gathered in figure 9.2.43. There is a large spread between maximum and minimum value in the coefficients and median values are close to zero. Furthermore, the coefficients are in general infrequently significantly different from zero when we llok at their t-values over time. Although capital intensity, beta and profit margin risk all were statistical significant, no statistically significant relationship between ROIC, reinvestment rate and EBIT growth on ln EV/EBITDA was found.

**Figure 9.2.43 - Summary statistics ln EV/EBITDA regression**

**Quarterly data**

| Adjusted R-squared | | | R-squared | CI† |
|---|---|---|---|---|
| Min. | Median | Max. | Median | #/total |
| -0.18 | 0.59 | 0.95 | 0.74 | 27/41 |

| Std. Error of Estimate | | | F-test | |
|---|---|---|---|---|
| Min. | Median | Max. | Median | # sig./total |
| 0.12 | 0.45 | 1.03 | 4.00 | 18/41 |

| Variable | Min. | Median | Max. | # sig./total | # VIF‡/total |
|---|---|---|---|---|---|
| Intercept | -60.67 | 0.72 | 78.23 | 14/41 | n.a. |
| ROIC | -6.47 | -0.00 | 50.47 | 3/41 | 0/41 |
| Reinvestment Rate | -13.56 | -0.00 | 16.51 | 4/41 | 2/41 |
| Capital intensity | -4.38 | 0.05 | 30.82 | 6/41 | 2/41 |
| EBIT growth | -345.12 | -0.01 | 11.92 | 3/41 | 3/41 |
| Beta | -15.92 | 0.00 | 183.03 | 5/41 | 2/41 |
| Profit margin risk | -348.05 | -0.02 | 25.25 | 9/41 | 3/41 |

# sig/.total: number of significant quarters of total (95% conf. level)

†: number of quarters with moderate to strong multicollinarity/value of condition index. Strong to moderate multicollinarity when 100<CI<1000

‡: quarters (#) with multicollinarity/variable is highly multicollinare when VIF>10

**Pooled data**

| # sample size | Adj. R-squared | F-test | Std.Error | CI† |
|---|---|---|---|---|
| 647 | 0.36 | 62.7*** | 0.84 | 52.69 |

| Variable | Coef. | VIF‡ |
|---|---|---|
| Intercept | 1.41*** | n.a |
| ROIC | -0.06 | 1.01 |
| Reinvestment Rate | -0.0002 | 1.00 |
| Capital intensity | 0.02** | 1.07 |
| EBIT growth | -0.019 | 1.00 |
| Beta | -0.036* | 1.03 |
| Profit margin risk | 1.51*** | 1.05 |

*Significant at 90 % confidence level.

**Significant at 95 % confidence level.

***Significant at 99 % confidence level.

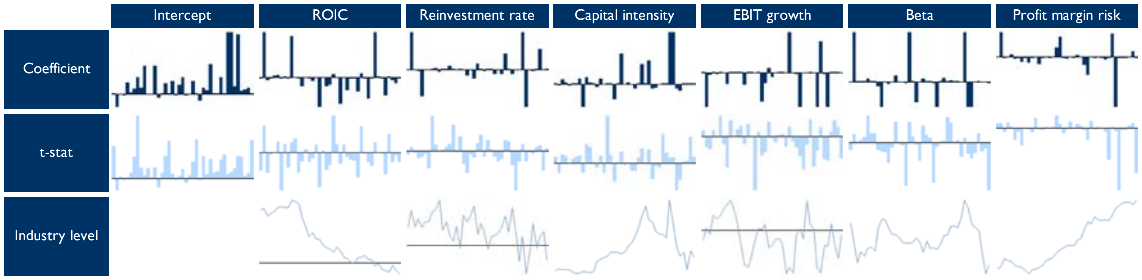
Source: Own Creation

The negative sign of beta is as expected by theory, but both the profit margin risk and the capital intensity coefficients are opposite of what was suggested by theory. Translating this to economic terms, investors are paying more for companies with a high level of operational expenditures and depreciation, while less for a high beta company. This is not that surprising if we think about what we uncovered in the industry analysis, where both the profit margin risk and the capital intensity were increasing relatively in line with the multiple, whereas the beta was depicting a more inverse relationship. Lastly, it should be noted that the profit margin risk appears highly economically significant because of the magnitude of the coefficient.

### *Trend summary of regression coefficients*

The summary chart perfectly illustrates the volatility of the coefficients. There is no stability and there are occasionally huge spikes in the coefficients, in addition to a low frequency of significance. See appendix 9.2.3 for detailed graphs.

**Figure 9.2.44 - Chart summary of trends in coefficients in ln EV/EBITDA regression**

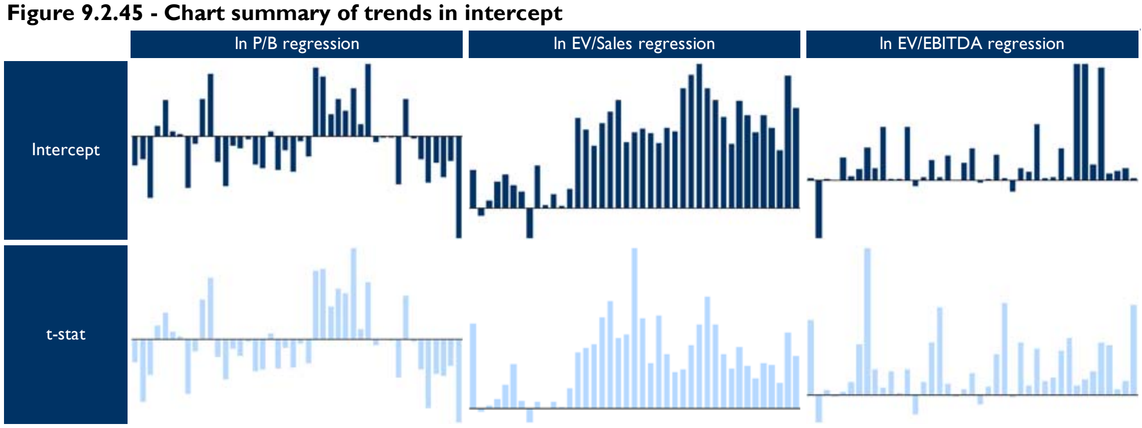



Source: Own creation

### Intercept discussion

The intercept in the ln P/B regression is not once significant at a 95% confidence level over the period, and is not depicting any particular trend. Even though the intercept in the ln EV/EBITDA regression is sporadically significant, it is hard to untangle any meaningful pattern. This is opposite to the intercept in ln EV/Sales regression, and as seen in figure 9.2.45, the intercept is almost exclusively positive. There has clearly been a change in the magnitude of the intercept, a change that is coinciding with the beginning of a negative trend in the freight rates and an overall reduction in the magnitude of the coefficients in the regression. The intercept is statically significant from 2010 until today (see appendix 9.2.3), and the "garbage collector" therefore evidently picks up some factors not incorporated by the model, but nonetheless affect investors' appraisal of the companies.

**Figure 9.2.45 - Chart summary of trends in intercept**




Source: Own creation

Since the coefficients in the EV/Sales have become less economically and statistically significant, the increase in the intercept can be seen as a manifestation of investors shifting away from the fundamental factors included in the model to other unexplained elements in 2009. In the quarters where the model has low explanatory power, the average multiple is probably just as good at forecasting value. Appendix 8.1 from the industry analysis showed that the median EV/Sales multiple increased since 2010, opposite of how the fundamentals and the freight rates have behaved. This behaviour may be explained by the elements we saw in section 5.4.2, where investors seemed to value cyclical companies with a mix of "perfect foresight" and "zero foresight". If investors are see through the downturn or factors in an upturn, the multiple will increase despite of worsen fundamentals. Thus, the increase in intercept may be viewed as investors' willingness to look further into the future than what is happening just in front of them, or in other words, they are abandoning the current accounting ratios and looking into a "brighter" future when evaluating the companies.

### Conclusive thoughts & hypotheses assessment

All things considered, it is reasonable to say that the quarterly regressions, with one exception, do not provide any broad support to the theoretically expected significance of the identified value drivers on the multiples. This is because the coefficients rarely are statistically significant, but bear in mind that the small sample sizes each quarter cause the insignificant coefficients to be weak evidence for the absence of effects (Allison, 1998, p. 57). Even though the sample size is small, we should take the significant coefficients seriously, and the EBIT-margin showed its prominence for the EV/Sales multiples in numerous quarters. However, both its economically and statistically significance tapered off simultaneous with the downward trend in both margins and freight rates five years ago. The decline in the significance of the EBIT-margin and the other coefficients supposed to explain the EV/Sales multiple coincide with an increase in the intercept, and it may be inferred that it is possible that the intercept captures an increased focus on future prospects at the expense of the current state.

The pooled regressions offer a much larger sample size and thus more precise estimates of the coefficients (Allison, 1998, p. 58), which should make us more confident when interpreting the significance of the coefficients. On the other hand, the detected relationship may not be representative for the current state, and it may take time before the relationship reverts back to its normal state, which can be a problem if an investment is undertaken on the basis of the pooled regression relationship and the holding period is short. The beta coefficients take on a negative sign in each of the pooled regressions, in line with the theoretically expected effect. However, capital intensity and profit margin risk, both statistically significant, depicts the opposite sign of what was expected by theory, but confirms what we saw in the industry analysis. Moreover, the FCFF-margin is also a statistically significant negative contributor to the EV/Sales multiple, while the P/B multiple is positively affected by the debt-to-equity ratio. That said, the abovementioned coefficients, except for the profit margin risk, have limited economically impact on the multiples. Regardless of the decline in the significance of the EBIT-margin the last couple of years, the pooled regression shows illustrates its positive impact on EV/Sales, though it is economically weak, but strongly statistically significant.

All hypotheses regarding the relationship between the multiples and the fundamentals in the dry bulk sector are presented in figure 9.2.46:

**Figure 9.2.46 - Assessment of dry bulk hypotheses**

| | | | ROE | ROIC | EBIT-margin | Growth | Capital intensity | Reinvestment rate | FCFF-margin | Beta | Profit margin risk | Op.liability risk | Debt to equity | Baltic Dry Index |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P/B | Overall | Hypothesis: | pos. | | | pos. | | | | neg. | neg. | pos/neg. | neg. | pos. |
| P/B | Quarterly | Mostly positive or negative? | pos. | | | pos/neg. | | | | neg. | pos. | pos/neg. | pos/neg. | |
| P/B | Quarterly | Mostly statistically significant? | × | | | × | | | | × | × | × | × | |
| P/B | Quarterly | Economically significant? | < 2012 | | | ✓ | | | | [2012;2015] | ✓ | ✓ | × | |
| P/B | Pooled | Positive or negative? | neg. | | | pos. | | | | neg. | neg. | neg. | pos. | pos |
| P/B | Pooled | Statistically significant? | × | | | × | | | | ✓ | ✓ | × | ✓ | ✓ |
| P/B | Pooled | Economically significant? | × | | | × | | | | × | × | × | × | ✓ |
| EV/EBITDA | Overall | Hypothesis: | | neg. | | pos. | pos. | neg. | | pos/neg. | pos. | | | pos/neg. |
| EV/EBITDA | Quarterly | Mostly positive or negative? | | pos/neg. | | pos/neg. | pos/neg. | pos/neg. | | pos/neg. | pos/neg. | | | |
| EV/EBITDA | Quarterly | Mostly statistically significant? | | × | | × | × | × | | × | × | | | |
| EV/EBITDA | Quarterly | Economically significant? | | × | | × | × | × | | × | × | | | |
| EV/EBITDA | Pooled | Positive or negative? | | neg. | | neg. | pos. | neg. | | neg. | pos. | | | neg [1] |
| EV/EBITDA | Pooled | Statistically significant? | | × | | × | ✓ | × | | ✓ | ✓ | | | × |
| EV/EBITDA | Pooled | Economically significant? | | × | | × | × | × | | × | ✓ | | | × |
| EV/Sales | Overall | Hypothesis: | | neg. | pos/neg. | pos. | | neg. | pos/neg. | pos/neg. | | | | pos/neg. |
| EV/Sales | Quarterly | Mostly positive or negative? | | neg. | pos | pos/neg, | | pos/neg. | neg. | pos/neg. | | | | |
| EV/Sales | Quarterly | Mostly statistically significant? | | × | ✓ | × | | × | × | × | | | | |
| EV/Sales | Quarterly | Economically significant? | | ✓ | < 2013 | × | | × | × | × | | | | |
| EV/Sales | Pooled | Positive or negative? | | neg. | pos. | neg. | | neg. | neg. | neg. | | | | pos [1] |
| EV/Sales | Pooled | Statistically significant? | | × | ✓ | × | | × | ✓ | ✓ | | | | × |
| EV/Sales | Pooled | Economically significant? | | × | × | × | | × | × | × | | | | × |

Pos/neg: indicates that the relationship shifts from period to period. Mostly statistically significant: ✓= most of the quarters are significant, ×=seldom significant.

Economically significant: < 2001 indicates that the coefficient has been signficiant until 2001, [2001;2005] = economcially significantly between 2000 and 2005, ✓=significant in most of the quarters, ×=seldom/never significant

[1] We have used the growth rate in BDI instead of the absolute BDI in the final regression model, which was both economically and statistically significant for the multiple.

Source: Own creation

## 9.3 MODEL REFINEMENT PROCESS

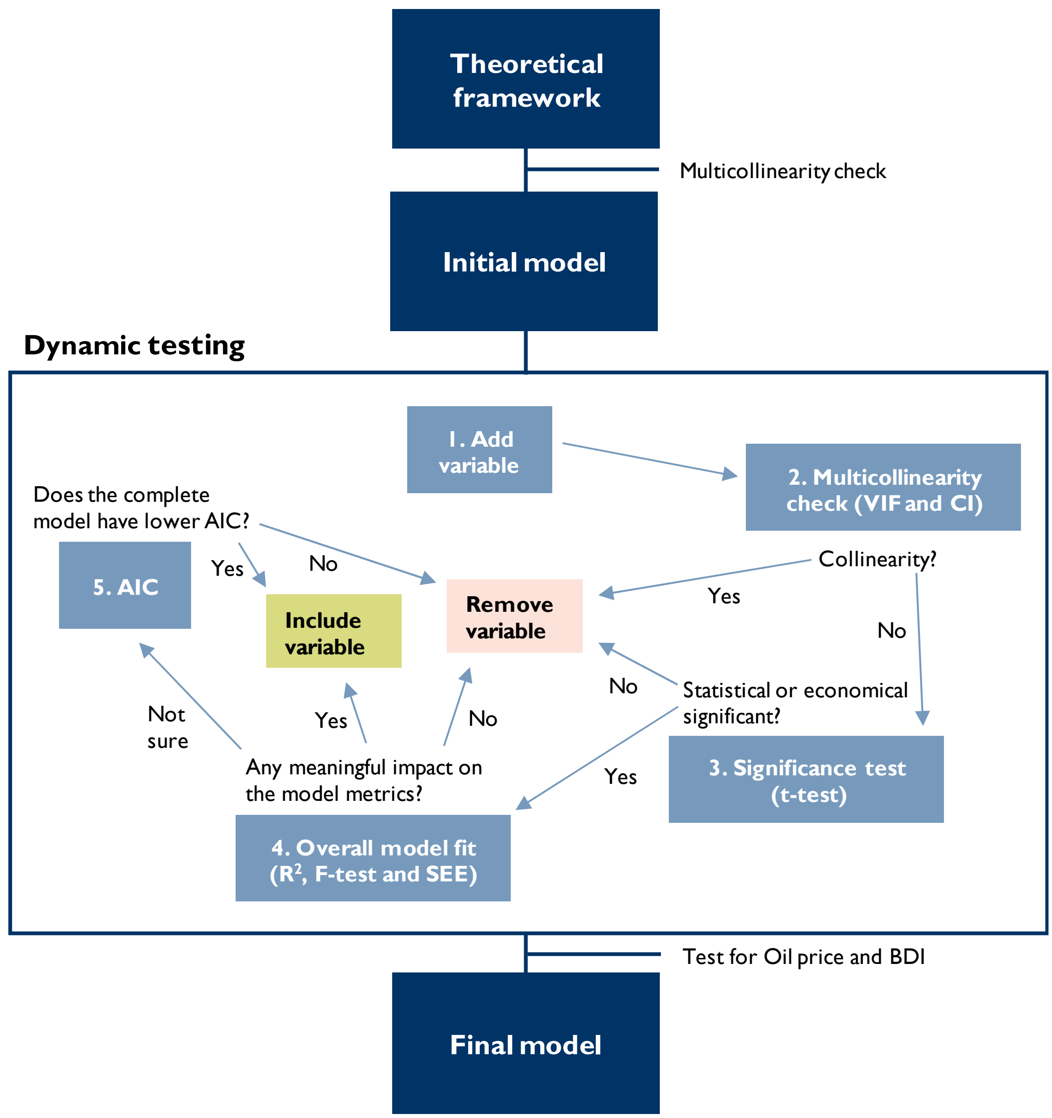
After the initial model has been established for each of the multiples in the E&P and dry bulk samples, we initiate a testing process, where variables are added to and removed from the models continuously as illustrated in figure 9.3.1. This is done in part to control for any endogeneity, such as omitted variable bias, but also to see whether there are more variables that can help us explain the variations in the dependent variable.

The first thing we do is to check for multicollinearity. If the variable is collinear to one of the already included variables, we run the whole dynamic testing process excluding the already included collinear variable too see whether the new collinear variable has any significant effects, and if it improves the overall fit of the model in comparison to the statistics levels before it was added to the regression.

Second, if the added variable does not display any form of collinearity, we review its significance levels. This is assessed by looking at its economically and statistically significance. We admit that an economical and statistical significant variable is preferable, but we include any variable that is statistically significant at a 1,5 or 10 pct. level.

Third, if the variable is economical or statistical significant, we analyse how the added variable affects the overall fit of the model, i.e. the adjusted R-squared, F-test and Standard error of the estimate. A meaningful impact on one or more of these metrics would prompt us to include the variable to our final model. If it does not provide any impact, we would go over the variable again to evaluate whether to include it regardless of the overall metrics, but we would most likely remove the variable. This process is repeated until all the additional variables are tested, which amounts to about 5-10 extra variables depending on the multiple. An overview of these variables are presented in figure 8.31.

**Figure 9.3.1 – Model refinement process**




Source: Own creation

Fourth, if we are not sure whether a variable adds any meaningful impact on the overall fit of the model, we perform a final check by comparing AIC for the complete model against the reduced model, where the included variable is set equal to zero. The model with the lowest AIC value is favoured.

Lastly, when all our company specific variables are tested and a final model is established, we carry out additional tests to investigate whether the natural logarithm of the Baltic Dry Index and the oil price are capable of explaining any of the variation in the multiples, which we suspected after our industry analysis and our coefficient analyses in the previous section. If they do not provide any meaningful improvement, we perform a final regression where we test the yearly moving average growth in BDI and the oil price instead of the absolute levels.

## 9.4 FINAL REGRESSION RESULTS

The dynamic refinement process presented above culminated into our final regression models, which either include the natural logarithm of BDI or the oil price, or growth in BDI, in addition to other variables that passed our refinement process in regards to multicollinearity, statistical and economic significance, and overall model fit.

### 9.4.1 DRY BULK RESULTS

Our model refinement process generated three regressions for dry bulk with six variables included at the most. Ln BDI was added to the ln P/B regression, but did not have any significance in explaining ln EV/Sales or ln EV/EBITDA. Thus, BDI growth was tested and successfully included in both regressions. As expected, both coefficients, ln BDI and BDI growth, display a positive relationship to their respective multiples. In addition, with their relatively high marginal impact on pricing multiples, they are not only statistically significant, but also economically significant, confirming our suspicions from the initial regression analysis in section 8 and our industry analysis in section 7. A summary of our pooled regressions is illustrated in appendix 9.4.1

It is particularly interesting to observe that the overall fit of the regressions models improved substantially on almost all of the overall metrics in figure 9.4.1. Adjusted $R^2$ for ln P/B, ln EV/Sales and ln EV/EBITDA increased from 0.02, 0.14 and 0.36 to 0.08, 0.19 and 0.41, while the F-stat improved and yet again confirmed the joint significance of the model at a 1 pct. level. However, when we examine the standard error of the estimate for EV/Sales, there is an unfortunate increase, although the rest of the model appears to have improved. It is also worth mentioning that even though our $R^2$ increased, it is still fairly low for all models, indicating that there are still some effects that our model is not able to detect.

Most variables included into the final models are highly statistical significant, but they also show tendencies of being more economic significant than some of the variables from the initial model. This has in turn appeared to reduce the value of the intercept for both P/B and EV/Sales, as more and more of the variation in pricing multiples are explained by the coefficients. Thus, it could be argued that some or most of the uptick in the adjusted $R^2$ is due to an increased economic significance in the coefficients.

**Figure 9.4.1 - Final regression model in Dry Bulk**

| ln P/B | | ln EV/Sales | | ln EV/EBITDA | |
|---|---|---|---|---|---|
| **Adj. R-squared** | 0.08 | **Adj. R-squared** | 0.19 | **Adj. R-squared** | 0.41 |
| **F-stat** | 26.49 *** | **F-stat** | 26.74 *** | **F-stat** | 69.6 *** |
| **Std. of estimate** | 1.41 | **Std. of estimate** | 0.89 | **Std. of estimate** | 0.82 |
| **Variable** | **Coef.** | **Variable** | **Coef.** | **Variable** | **Coef.** |
| **Intercept** | -3.13 *** | **Intercept** | 0.86 *** | **Intercept** | 2.80 *** |
| **Beta** | -0.057 *** | **Beta** | -0.029 * | **Beta** | -0.069 ** |
| **Sales growth** | 0.53 ** | **EBIT growth** | 0.008 *** | **EBIT growth 3yr** | 0.0051 *** |
| **FCFF-margin** | 0.042 *** | **FCFF-margin** | -0.084 *** | **FCFF-margin** | -0.14 *** |
| **ln BDI** | 0.46 *** | **EBITDA-margin** | 0.59 *** | **EBITDA-margin** | -1.36 *** |
| | | **ROE** | 0.007 *** | **Capital intensity** | 0.026 ** |
| | | **BDI growth** | 0.90 *** | **BDI growth** | 0.63 ** |

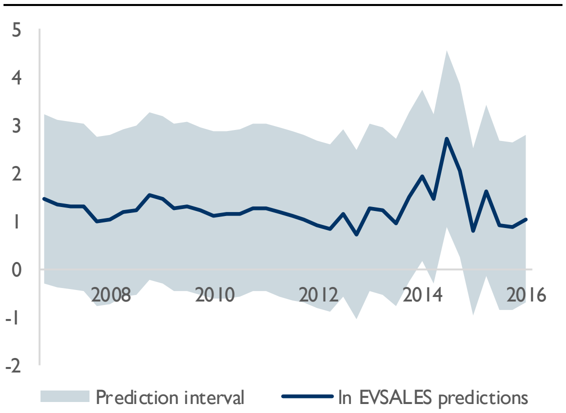
Source: Own creation

Significance level: *** 0.01 ** 0.05 * 0.1

The prediction interval in figure 9.4.2 displays where the actual ln EV/Sales value for the dry bulk company, Golden Ocean (GOGL), should be situated with a 95% probability. If we look at our prediction for fourth quarter of 2016 at 1.05 or 2.85 exposed, there is a 95% chance that the actual value can lie between – 0.71 and 2.80 or 0.49 and 16.52 exposed. Although we would have wished that the interval was more compact, it underpins the uncertainty of our predictions.

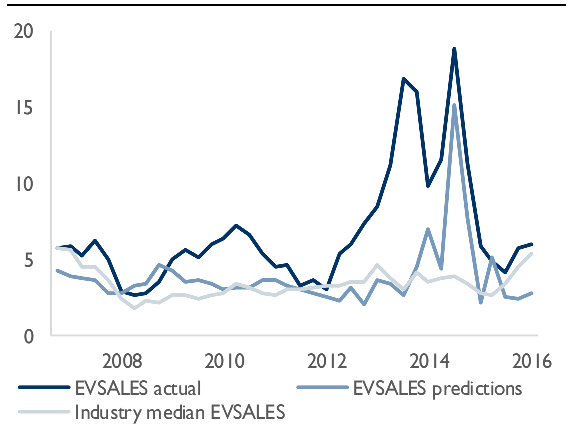
Despite the uncertainty of our predictions, it is interesting to compare our predictions to GOGL's actual EV/Sales levels. Since the model is based on market valuations of the sector and controls for differences in the explanatory variables among the firms, a higher or lower predicted multiple than the actual value implies that the market is mispricing the company relatively to the sector. According to our model, GOGL is expensive from 2007 to 2009, before it turns cheap in the first three quarters of 2009, and then remains expensive all the way to 2016. Thus, it is appealing to see that our model is able to generate both overvalued and undervalued signals as opposed to the industry median, which states that GOGL is constantly too expensive.

**Figure 9.4.2 - GOGL prediction interval**




Source: Own creation

**Figure 9.4.3 - GOGL EV/Sales predictions**




Source: Own creation

The analysis in the prior sections pointed out that a model with coefficients that are economically or statistically insignificant, but with an intercept that is significant, will have an intercept that is close to the mean industry multiple. Although our EV/Sales predictions and the other multiple predictions displayed in appendix 9.4.1 tend to fluctuate around the same level as the industry median, the EV/Sales predictions clearly deviate from the median enough for us to establish economic significance. But do our predictions make any sense? If we move over to figure 9.4.4, we have constructed a table where each variable in the ln EV/Sales regression, including the multiple itself, are ranked into percentiles from 10% to 90%. Even though this percentile table analysis is not a normal procedure when performing a regression analysis, as it is implicit in the nature of the technique, it is still a great tool for reality and diagnostic checks.

Our EV/Sales prediction for GOGL at 1.05 lies somewhere between the 30th and 40th percentile. Seen against an ROE in the 60th percentile, EBITDA-margin in the 40th percentile, and Beta, EBIT growth and FCFF-margin in the 10th and 20th percentile, we find it reasonable to argue for a valuation just under the median at the 50th percentile. Thus, our model appears to yield more consistent results than a simple median valuation would, further reinforcing the robustness of the model. Similar results can also be observed in our P/B predictions for GOGL in appendix 9.4.1, but the model on EV/EBITDA is more ambiguous, with a 90th percentile prediction when several of the included variables lies below the 50th percentile.

**Figure 9.4.4 - GOGL in ln EV/Sales Dry Bulk regression variables percentile distribution (2016Q4)**

| Percentile | LN_EVSALES | ROE | EBITDA-margin | Beta | EBIT growth 3yr | FCFF-margin |
|---|---|---|---|---|---|---|
| 10% | -0.12 | -49.88 | -1.66 | 32.80 | **-1.97** | **-1.45** |
| 20% | 0.60 | -0.75 | -0.63 | **0.52** | -1.36 | **-0.25** |
| 30% | **0.99** | -0.45 | -0.38 | 0.48 | -0.68 | 0.20 |
| 40% | **1.11** | -0.42 | **-0.14** | 0.19 | -0.40 | 0.54 |
| 50% | 1.37 | -0.30 | 0.00 | -0.24 | -0.30 | 0.60 |
| 60% | 1.69 | **-0.17** | 0.04 | -0.34 | -0.27 | 0.85 |
| 70% | 1.76 | -0.13 | 0.14 | -0.53 | -0.20 | 1.20 |
| 80% | 1.80 | -0.06 | 0.26 | -0.77 | 0.03 | 1.68 |
| 90% | 2.29 | 0.02 | 0.59 | -1.29 | 0.05 | 6.26 |

Source: Own creation

### 9.4.2 E&P RESULTS

Unlike in the dry bulk industry, the industry specific driver, ln oil price, were both economical and statistical significant for all regressions on the E&P sector. We tested for oil price growth as well, but it did not yield satisfactory results. Nonetheless, as we anticipated from our industry analysis, the oil price is positive correlated with the pricing multiples, which means that an increase in the oil price will ceteris paribus increase the multiple for the relevant company. A summary of our pooled regression can be found in appendix 9.4.2.

Despite our efforts to improve the regression models by including, removing and transforming variables, the $R^2$ is still not impressive as seen in figure 9.4.5, ranging from as low as 0.02 to 0.05. Consequently, there are a lot of variation in the pricing multiples that our models are not capable of explaining, which is why the intercept remains strong for ln P/E and ln EV/EBITDA, even though it is losing some power from the initial to the final regression model. It should also be noted that a low $R^2$ is very common in these types of regressions where the dependent variable is a ratio, and we could have achieved a much higher $R^2$ if we applied an absolute dependent variable instead (Abrams J. B., 2012, p. 10)

Although adjusted $R^2$ is still low, it has increased by a substantial amount compared to our initial regression model. Similarly, the standard error of the estimate was reduced by between 10-30% for all four regression models. In addition, ln P/B and ln EV/EBITDA have seen a significantly decrease in their intercepts. This indicates that we have successfully included several economic and statistical significant variables, such as the oil price, which have reduced the amount of "garbage" in the "garbage collector". As seen in the tables below, the oil price is clearly the number one driver for the multiples in the E&P industry. It should also be noted that many of the variables in the final models have a rather low economically significance, but that they are all statistically significant. We could have considered to remove them, but due to their statistically significance and theoretically backing, we choose to keep them in our model.

**Figure 9.4.5 - Final regression model in E&P**

| ln P/B | | ln P/E | | ln EV/Sales | | ln EV/EBITDA | |
|---|---|---|---|---|---|---|---|
| Adj. R-squared | 0.030 | Adj. R-squared | 0.023 | Adj. R-squared | 0.053 | Adj. R-squared | 0.046 |
| F-stat | 75.22 *** | F-stat | 23.04 *** | F-stat | 48.95 *** | F-stat | 81.35 *** |
| Std. of estimate | 2.13 | Std. of estimate | 2.03 | Std. of estimate | 1.64 | Std. of estimate | 1.49 |
| **Variable** | **Coef.** | **Variable** | **Coef.** | **Variable** | **Coef.** | **Variable** | **Coef.** |
| Intercept | -1.49 *** | Intercept | 1.24 *** | Intercept | -1.62 *** | Intercept | 0.57 *** |
| Book value growth 5yr | 0.028 ** | Sales growth 5yr | 0.00058 ** | NOPAT growth 5yr | 0.0017 *** | Sales growth 5yr | -0.00079 *** |
| FCFF-margin | 0.00014 *** | FCFF-margin | 0.00045 * | ROIC | -0.054 *** | ROIC | -0.0066 * |
| EBITDA-margin | 0.0013 ** | EBITDA-margin | 0.30 ** | EBITDA-margin | -0.025 *** | Capital intensity | 0.053 *** |
| ln Oil price | 0.55 *** | Beta | -0.0044 * | Reinvestment rate | 0.00017 *** | ln Oil price | 0.36 *** |
| | | ROIC | 0.0075 ** | ln Oil price | 0.55 *** | | |
| | | ln Oil price | 0.32 *** | | | | |

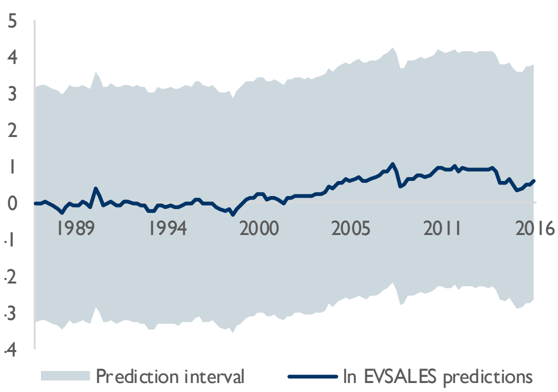
Source: Own creation

Significance level: *** 0.01 ** 0.05 * 0.1

It is not surprising that our prediction intervals for the oil company, Energen (EGN), displayed in figure 9.4.6 have fairly wide intervals as it is quite challenging to produce predictions that are reasonably precise with an adjusted $R^2$ of 0.053. In the fourth quarter of 2016 our ln EV/Sales prediction for EGN came in at 0.58 or 1.78 exposed, with a 95% probability that the actual value is between -2.65 and 3.80, or 0.07 and 44.56 exposed. Compared to the prediction interval for GOGL, one would perhaps expect a narrower band for EGN due to the larger sample size in the oil regression. However, the central limit theorem does not benefit the prediction interval the same way it benefits the confidence interval. This is because the central limit theorem is related to central tendencies, and not to individual behaviour or outcomes. In other words, individual behaviour, such as our company predictions, remains uncertain regardless of how much you increase your sample size.

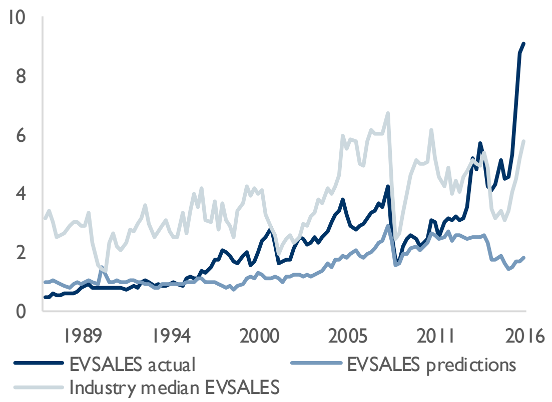
According to our model, EGN is undervalued from the first quarter of 1987 to the first quarter of 1993, before it changes back and forth from overvalued and undervalued until the third quarter of 1995, and from that point in time EGN remains overvalued compared to the sector. Similar graphs can be found in appendix 9.4.2, although the predictions can vary quite a lot depending on the company in focus and multiple used for predictions.

**Figure 9.4.6 - EGN prediction interval**




Source: Own creation

**Figure 9.4.7 - EGN EV/Sales predictions**




Source: Own creation

Similarly, to our GOGL EV/Sales predictions, the EGN predictions deviate from the industry median, but the EV/Sales predictions for EGN remain much more stable in comparison. This could in part be because the model is able to see through the cyclical behaviour of the stock market and the industry, but it may also be a consequence of a highly dominating intercept. However, since the predictions clearly increase over time, there are also some coefficients that affect the multiple, and we saw earlier that the oil price coefficient had a decent economically impact on the multiple. This is illustrated by how the EGN EV/Sales predictions pick up momentum at the same time as the oil price starts to rise in the early 2000s, and how the intrinsic multiple increases from 1 to about 2.5.

In order to further investigate the predictive power of our regression, we have also created a percentile table for the EV/Sales E&P regression, although with 5-percentile intervals. Our model yields an ln EV/Sales multiple between the 30$^{th}$ and 35$^{th}$ percentile, but the variables included in the model signals that EGN deserves a somewhat higher multiple (40$^{th}$ percentile if we average out the percentiles for the variables included). Anyway, the model yields a better estimate than just applying the simple average/median, because it acknowledges that the company underperforms the average company in the sector when it comes to the fundamentals controlled for in our model. There are also some encouraging outcomes in ln P/B and ln EV/EBITDA, which do not only display a diminishing intercept, but also demonstrate plausible results in the percentile distribution table in appendix 9.4.2. For example, a low predicted ln P/B is accompanied by a low ROIC and Sales growth 5yr in the fourth quarter of 2016.

**Figure 9.4.8 - EGN in ln EV/Sales E&P regression variables percentile distribution (2016Q4)**

| Percentile | LN_EVSALES | ROIC | EBITDA-margin | Reinvestment rate | NOPAT growth 5yr |
|---|---|---|---|---|---|
| 1% | -3.48 | -14.56 | -144.80 | 70.64 | -11.99 |
| 5% | -1.29 | -1.26 | -1.85 | **4.42** | -2.92 |
| 10% | -1.00 | -0.57 | -1.19 | 3.23 | -1.55 |
| 15% | -0.83 | -0.34 | -0.75 | 2.83 | -1.01 |
| 20% | -0.53 | -0.23 | -0.46 | 2.36 | -0.65 |
| 25% | -0.39 | -0.14 | -0.23 | 1.91 | **-0.30** |
| 30% | **0.42** | -0.10 | 0.01 | 1.51 | **-0.19** |
| 35% | **0.70** | -0.07 | 0.05 | 1.39 | 0.06 |
| 40% | 1.25 | -0.06 | 0.07 | 1.27 | 0.07 |
| 45% | 1.51 | **-0.05** | 0.08 | 1.15 | 0.15 |
| 50% | 1.61 | -0.03 | 0.10 | 1.05 | 0.24 |
| 55% | 1.64 | -0.01 | 0.10 | 0.96 | 0.34 |
| 60% | 1.79 | 0.01 | 0.13 | 0.83 | 0.53 |
| 65% | 1.87 | 0.05 | 0.14 | 0.32 | 0.83 |
| 70% | 1.97 | 0.06 | 0.21 | 0.11 | 1.16 |
| 75% | 2.21 | 0.09 | 0.27 | -0.16 | 2.03 |
| 80% | 2.36 | 0.12 | 0.33 | -0.31 | 2.52 |
| 85% | 3.02 | 0.17 | **0.42** | -1.89 | 3.38 |
| 90% | 3.99 | 0.24 | 0.49 | -4.12 | 6.06 |
| 95% | 4.62 | 0.56 | 0.53 | -11.52 | 8.78 |
| 99% | 8.86 | 6.60 | 0.74 | -46.21 | 20.53 |

Source: Own creation

### 9.4,3 WEIGHTED R-SQUARED VALUATION

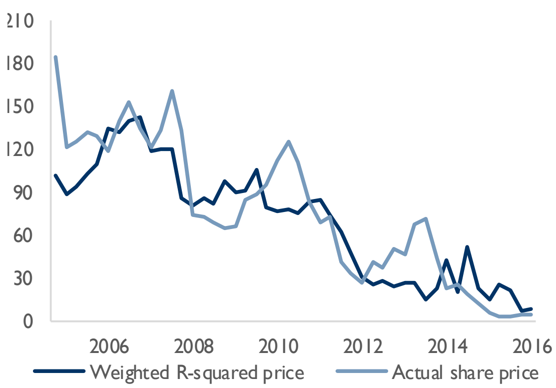
Although there are a lot of flaws associated with the adjusted R-squared metric, and it is not completely reliable when compared across a set of models with different dependent variables and data samples, its standardised measure is still attractive as a method to harvest the benefits from several regression models. Hence, we argue that by constructing a weighted average of the different pricing multiples models with the adjusted R-squared metric, it can stimulate to a smoother and more robust result. One could of course have argued for a simple average as well, but we believe that weighting the different models on their ability to explain the variance in their dependent variable will yield superior results. The weighted R-squared price is calculated as follows:

$$Weighted\ R^2\ price = \sum \frac{Predicted\ multiple \cdot Adj. R^2 \cdot Performance\ measure}{Shares\ outstanding \cdot \sum Adj. R^2}$$

As seen by the formula, the weighted R-squared price is estimated by multiplying each predicted multiple with its related performance measure (for example "sales" in the EV/Sales multiple), and this price is then weighted by the model's adj. R-squared before it is divided by the company's shares outstanding to display the value on a per share basis.

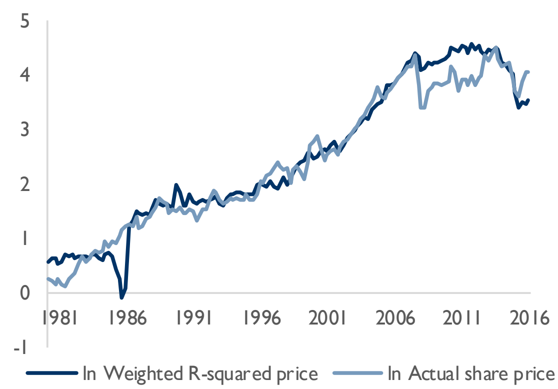
The estimated weighted R-squared price for GOGL and EGN each quarter is illustrated in figure 9.5.1 and 9.5.2, and because of a substantial price development in EGN over the last 35 years we have added the logarithmic value of EGN's share price to put special emphasis on the historical price movements. Individually, the models gave us some mixed results. For instance, the E&P ln EV/Sales predictions on EGN constantly stated that EGN was overvalued. Combined, through the R-squared weighting, the E&P models' predictions appear much more robust and less volatile, but still capable of creating under- or overvalued signals, regularly. The model tracks the actual share price remarkably well, and it is especially interesting to observe how our model is also able to see through the cycle in the aftermaths of the financial crisis in 2008, when stock prices and earnings fell, but quickly recovered by 2012. Similar results can also be drawn from the dry bulk weighted R-squared valuation for GOGL, which displays a smoother development in comparison to each of the models individually. It is important to point out that the model consolidation is not held accountable for this effect alone, but in combination with the effect from controlling for the performance measure, which is known for its volatile nature.  As an example, the share price may trade at "normal" levels, but if the earnings are extremely low, the multiple would be just as extremely inflated. Thus, by controlling for the extremely low earnings in the multiple the share price, and the valuation outlook would return back to normal.

**Figure 9.4.9 - Weighted R-squared price GOGL**




Source: Own creation

**Figure 9.4.10 - Weighted R-squared price EGN**




Source: Own creation

### 9.4.5 CONCLUSIVE THOUGHTS ON FINAL REGRESSION RESULTS

Our refinement process clearly benefitted the overall fit of the models and confirmed our suspicions that the oil price and BDI would stand out as two important drivers of the multiples. Still, the regression models appear to be haunted by a low R-squared. Although this is not unlike other similar regression analyses in research papers, it still demands the appropriate attention. It is difficult to determine exactly what causes the low R-squared, but with some certainty, it appears to be a blend of outliers and missing variables. Nevertheless, our prediction charts and percentile distribution tables show that our models are capable of effectively controlling for differences between firms, where a median/mean multiple would contribute to an inaccurate valuation. Moreover, the models boast with a solid joint significance and both economically and statistically significantly coefficients that contain useful and important information. This is especially noticeable when we combine all the models in a weighted R-squared valuation, and we observe that the models are capable of continuously create under- and overvalued signals in both the dry bulk and E&P sector. The problematic part is however when the models are used for out-of-sample predictions, where the uncertainty of our predictions would be very high, due to the low R-squared and high standard error of the prediction. Thus, special cautions or further improvements should be made before one venture into out-of-sample forecasting.

# DISCUSSION

## E&P SECTOR

### THE STORY OF THE LOST DECADES

The early 2000s mark a turning point in the E&P sector, especially if we look at the P/B and the EV/Sales multiples. Market values and book values have been detaching and the multiples have skyrocketed, at the same time as the industry accounting returns and magnitude of the coefficients have been deteriorating and the intercepts in the regressions have been increasing. We argue that the continuing rise in the oil price from that point in time has contributed to a structural shift away from accounting ratios and left the two last decades fallowed in the eye of the fundamentalist. The refined models, which include the oil price, support the importance of the oil price in investors' assessments of the E&P companies through a reduction of the intercept and an increase in the adjusted R-squared. Our positive oil price coefficient is also opposite of the oil price coefficient Osmundsen et al. (2006) estimated in their regression, and does not confirm their hypothesis about investors' dependency on mid-cycle oil prices.

The witnessed drop in economically significance can be a sign of a change in investor behaviour, where expectations of future results outweighs the historical results in the investment process or they have become more sophisticated and increased their focus on asset valuations. It is probably also foolish to think that current returns are a good indicator of the future in a volatile industry like the E&P sector, but it is not that strange given the long lasting bull market in the oil price we have experienced the last two decades. However, since the industry's accounting returns have been in a declining trend almost ever since the oil price trend took off, it seems like investors are completely ignoring them in hope of a turnaround in the future - they have now waited for almost two decades.

## DRY BULK SECTOR

### LAND AHOY!?

Both the EV/Sales multiple and the EV/EBITDA multiple in the dry bulk sector has been in an upward trend the last four years in contrast to the negative trend in the industry profitability and accounting returns seen over the same period, which coincides with the falling freight rates. The P/B multiple has followed the freight rates and the industry profitability down, while the P/E is depicting a more side-ways evolvement. The coefficients in the dry bulk sector have not shown a similar simultaneous trend as seen in many of the coefficients in the E&P sector, but the EBIT-margin coefficient in the EV/Sales experiences a similar drop in significance in 2012, and the intercept is picking up some new effects, indicating that investors are abandoning the EBIT-margin as a sign of value creation.

We argue that the counterintuitive strong multiples are due to investors ability to look further into the future, incorporating a turnaround in their assessment of the companies, or maybe a normalisation. Thus, if we included some forward-looking fundamentals there is a good chance that we would have been able to get a more solid explanatory power. Anyway, someone on the dry bulk ship has shouted "Land Ahoy!", and the question is now when the ship actually encounters the promised land.

## MULTIPLES INVERSELY RELATED TO THE CYCLE

Figure 5.4.3 in the theory section illustrated a conceptualised expansion and contraction pattern inversely related to the cycle. This conceptualised pattern is visible in many of the estimated coefficients in our regressions, especially in the earnings multiples. There is a statistical negative relationship between EV/Sales multiples and NOPAT-margins, ROIC and growth, between EV/EBITDA multiples and ROIC and between P/E multiples and ROE in the E&P sector. Similarly, there is a negative relationship between EV/Sales multiples and cash flow-margins and between EV/EBITDA multiples and EBITDA-margins in the dry bulk sector. These negative coefficients indicate that investors to some degree are able to look past the current noise and factor in future prospects.

## REGRESSION RESULTS

According to a rule of thumb from Nau (2017), a model with a R-squared of 10% would have errors that are only about 5% smaller on average than those of an intercept-only model, which simply predicts that everything will equal the mean. This R-squared is not far from our own regression model results, but as our prediction charts and percentile distribution tables shows, both our E&P and dry bulk regressions are capable of effectively controlling for differences between companies. This is also supported by a highly significant F-test and several economic and statistical significant coefficients, and indicates that our models are better at predicting than the median/mean. However, the problem with a high standard error and low R-squared really starts to really materialise itself when we want to perform out-of-sample predictions, where the uncertainty of our predictions would be excessively high.

It is difficult to determine exactly what causes the low R-squared and high standard errors, but it appears to be a blend of outliers, and missing values, if we assume that our logarithmic transformation of the dependent variable is correct. Although outliers should take some blame for the heteroscedasticity and weak normality in our data sets, it is troublesome to eliminate some or all (apart from the clear flaws), because we risk venturing into data mining and losing valuable information. Moreover, despite our efforts to reduce missing variables during the refinement process, there are clearly other elements that explain the variation in the dependent variables, alongside the oil price and the BDI, that our model is missing, but further analysis would be required to uncover such information.

# CONCLUSION

This thesis has tracked investor behaviour across time with a specific focus on how they assess theoretical fundamental determinants when valuing companies in the highly volatile universes of dry bulk and E&P. The two words "unstable" and "fluctuating" would probably be some of the most prominent words in a word cloud of this thesis, as investors in dry bulk and E&P are exhibiting the same erratic behaviour as the companies they invest in. This observation is based on our extensive regression analysis of multiples and fundamentals from the early eighties until today, which quantifies and highlights how investors have changed their perception of important fundamentals from one period to another.

The theoretically expected relationship between the multiples and the identified fundamental determinants was ambiguous on a quarterly basis, due to the instability of the coefficients and variability in the statistically significance. Nevertheless, the results from the regression were often in line with the hypothesised directional impact on the multiples. However, "not statistically" significant and "not economically" significant were a general tendency in the quarterly analysis, which indicates that the identified drivers do not have a meaningful impact on the multiples. Still, some fundamentals were periodically encouraging in explaining the variations. The return on equity was a key driver for the P/B multiple in the E&P industry from 1980 until early 2000s, while the EBIT-margin showed its prominence for the EV/Sales multiple in dry bulk from 2006 until 2012. We argued that the oil price hike in the early 2000s and the downward trend in the freight rates could be plausible explanations for the observed strong drop in economically significance. Similarly, the pooled regressions, covering the entire period, confirmed many of our expected relationships, but several of our theoretical determinants failed to be both statistically and economically significant at the same time, with the profit margin risk as one of the few exceptions.

In our attempt to construct a set of multi-linear regression models to value any firm in the E&P and dry bulk sector, we refined the model to include significant determinants exclusively, including the oil price and BDI. The oil price was found to hold both an economically and statistically significant positive impact on the E&P multiples, while the BDI failed to be significant for two out of three multiples. However, the growth in BDI proved to be important for EV/Sales and EV/EBITDA in the dry bulk sector, and was thus included in the model.

Although our models appear to be haunted by a low R-squared and mixed economic significance, the F-stat displays a joint significance at a 1% level, and our prediction charts and percentile distribution tables illustrates that our models are capable of effectively controlling for differences between firms, where a median/mean multiple would contribute to an inaccurate valuation. This is also apparent in our weighted R-squared valuation, where our predictions appear much smoother and more robust than they would have by applying the models individually. Moreover, we observe that the weighted R-squared models are capable to continuously create under- and overvalued signals in both the dry bulk and E&P sector.

The results from this thesis may be valuable for anyone who wants to get a deeper understanding of how fundamentals are valued by the market in two industries known for extensive fluctuations, in both market values and financials. Moreover, it could also be valuable for investors who are looking for a way of controlling for differences when they are evaluating companies.

## FUTURE RESEARCH

Our low adjusted R-squared and high standard deviation pinpoints the fact that we are missing some explanatory factors in our models. Future research on this topic should therefore try to expand the data set to include other variables that may have an explanatory power on how the market is pricing companies in the E&P and dry bulk sector. We have in several occasions argued that investors may be incorporating future prospects different from the historical values in their assessment of valuing companies. A natural starting point would therefore be to include forward-looking consensuses estimates. The rotation away from accounting ratios in the E&P sector and low economically significance for the accounting ratios suggested by theory in both sectors, should encourage future research to include more sector specific accounting ratios, for instance reserve sizes, reserve replacement ratios, fleet sizes etc. Since the coefficients are quantitative expressions of investor behaviour, it would also have been interesting to interpret the coefficients from a behavioural finance point of view as well. Lastly, future research should consider including an analysis of a sector known to be stable and mature in order to see if there are any visible differences.

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# APPENDIX

## APPENDIX 7 DATA & CONSTRUCTION OF DATA BASE

### APPENDIX 7.1 - SCREENING STRATEGY BLOOMBERG

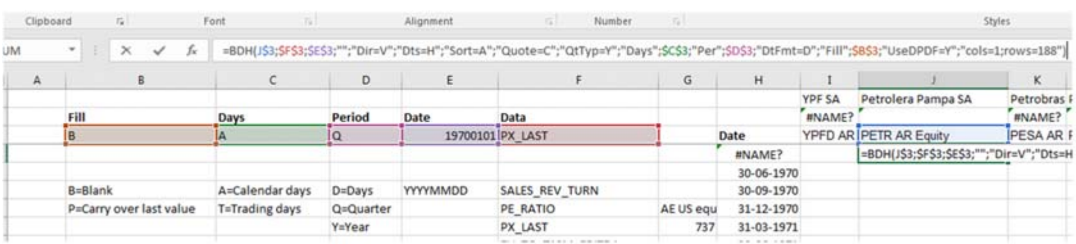


Source: Bloomberg

## APPENDIX 7.2 – COMPUSTAT VARIABLES

Current Assets - Total
Non-Current Assets - Total
Assets - Total
Common/Ordinary Equity - Total
Cash and Short-Term Investments
Debt in Current Liabilities
Long-Term Debt - Total
Depreciation and Amortization - Total
Income Before Extraordinary Items
Current Liabilities - Total
Liabilities and Stockholders Equity - Total
Operating Income After Depreciation - Quarterly
Operating Income Before Depreciation - Quarterly
Revenue - Total
Income Taxes - Total
Operating Expense- Total
Investing Activities - Net Cash Flow
Operating Activities - Net Cash Flow

## APPENDIX 7.3 – EXAMPLE OF PRICE DATA EXTRACTION FROM BLOOMBERG ADD-IN



## APPENDIX 7.4 - E&P DATA SAMPLE AFTER BLOOMBERG SCREENING AND COMPUSTAT (BLOOMBERG TICKERS)

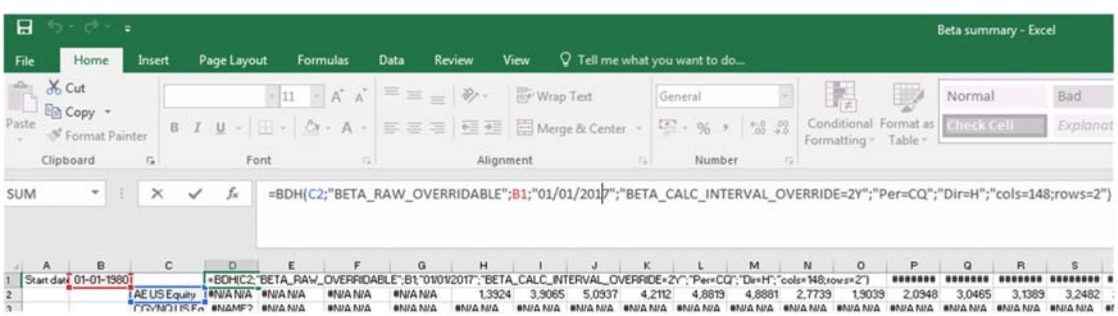
| | | | | | |
|---|---|---|---|---|---|
| AE US Equity | HNR US Equity | EPM US Equity | ROYT US Equity | SNREQ US Equity | MPO AU Equity |
| CGYNQ US Equity | BPT AU Equity | HDYN US Equity | USO CN Equity | USFCQ US Equity | FANG US Equity |
| APA US Equity | LNCOQ US Equity | SYNM US Equity | HK US Equity | WPX US Equity | ZAZA US Equity |
| ATU CN Equity | WGP US Equity | ALV CN Equity | SCEY US Equity | ECCE US Equity | ARPJQ US Equity |
| TREC US Equity | EOG CN Equity | SVSSF US Equity | IFR CN Equity | BCEI US Equity | BDCO US Equity |
| BRN US Equity | NSLPQ US Equity | CRZO US Equity | BBEPQ US Equity | MCEP US Equity | LLEX US Equity |
| BNE CN Equity | AVOA US Equity | SLG CN Equity | XOP CN Equity | MTDR US Equity | LPRIQ US Equity |
| MTZ CN Equity | PTRC US Equity | CBIS US Equity | EVEP US Equity | LPI US Equity | VOC US Equity |
| EMEX US Equity | AEGG US Equity | SNRNQ US Equity | TOU AU Equity | SN US Equity | XBOR US Equity |
| CDH CN Equity | JONE US Equity | ASRPF US Equity | PEY CN Equity | HBMK US Equity | KOS US Equity |
| CTNR US Equity | ATHL US Equity | MILLQ US Equity | SPP US Equity | MEMP US Equity | MRPL IN Equity |
| CVR CN Equity | EPE US Equity | BPIGF US Equity | IDNG US Equity | PBF US Equity | ESOIL IN Equity |
| CLR US Equity | RSPP US Equity | FPP US Equity | TAMO US Equity | DUNRQ US Equity | SOC PM Equity |
| CR CN Equity | PRK CN Equity | BXE CN Equity | UTOG US Equity | GPRK US Equity | MRL IN Equity |
| AOI CN Equity | RICE US Equity | UPLMQ US Equity | PGF CN Equity | PACD US Equity | JKX LN Equity |
| DMLP US Equity | PHX US Equity | GMNI US Equity | TOO CN Equity | ATH CN Equity | VET CN Equity |
| ESCRQ US Equity | ERF CN Equity | GGLR US Equity | MVO US Equity | SXY AU Equity | HME CN Equity |
| EGN US Equity | PSTRQ US Equity | KWKAQ US Equity | EPS CN Equity | SSN AU Equity | DOMR US Equity |
| EQT US Equity | PE US Equity | HGT US Equity | REI US Equity | SQZ LN Equity | EUGS US Equity |
| HKNI US Equity | ECR US Equity | CBNRQ US Equity | SD US Equity | STO AU Equity | TGC US Equity |
| HFC US Equity | VNOM US Equity | EW CN Equity | IAE CN Equity | PETRONM MK Equity | PRIO3 BZ Equity |
| ISRL US Equity | PBFX US Equity | FOSI US Equity | PEH CN Equity | WPL AU Equity | JUB LN Equity |
| JEC CN Equity | COG US Equity | PCO CN Equity | CXO US Equity | SHELL MK Equity | MOIL LN Equity |
| PNRG US Equity | DNR US Equity | RYPE US Equity | REXX US Equity | BPT AU Equity | PROS NO Equity |
| NESS US Equity | CRC US Equity | GSXN US Equity | SPI CN Equity | PMO LN Equity | QGEP3 BZ Equity |
| RRC RO Equity | PTXP US Equity | OBQI US Equity | OMTK US Equity | EEG AU Equity | NEW LN Equity |
| MPET US Equity | TVLYQ US Equity | ATPAQ US Equity | CVI US Equity | 5017 JP Equity | GENL LN Equity |
| MRO US Equity | MCF US Equity | NOG LN Equity | VNR US Equity | 5012 JP Equity | OPHR LN Equity |
| MEI CN Equity | RMP AU Equity | GMXRQ US Equity | GRO CN Equity | NZR NZ Equity | TRIN LN Equity |
| XCO US Equity | EESV US Equity | PWDR US Equity | AREX US Equity | CNE LN Equity | HIBI MK Equity |
| MUR US Equity | ESTE US Equity | FEECQ US Equity | SYRG US Equity | 1663 JP Equity | GNG IN Equity |
| NBL US Equity | CKX US Equity | PCQ CN Equity | GST US Equity | CTX AU Equity | 1251 HK Equity |
| OAKR US Equity | RSRV US Equity | CPG CN Equity | SCZ CN Equity | NZO NZ Equity | MAGP LN Equity |
| OXY US Equity | CRK US Equity | TMYEQ US Equity | TAO CN Equity | FAR AU Equity | RPO LN Equity |
| PVAC US Equity | BSM US Equity | SCUEF US Equity | SMB CN Equity | PGY AU Equity | ESSA IJ Equity |
| PBT US Equity | AXAS US Equity | HTOG US Equity | REN US Equity | UNAF UZ Equity | PVD AU Equity |
| PDCE US Equity | SPND US Equity | HUSA US Equity | WES US Equity | 883 HK Equity | KPL AU Equity |
| PNY CN Equity | SGL CN Equity | TNP AU Equity | DOY CN Equity | BND AU Equity | NOFL IN Equity |
| EDVC US Equity | OPMZ US Equity | SRX CN Equity | HECCQ US Equity | RDGZ KZ Equity | ISOPL IT Equity |
| SBR US Equity | PQ US Equity | NKO CN Equity | ART CN Equity | NOG LN Equity | KANI IN Equity |
| SJT US Equity | SM US Equity | XEC US Equity | DUCP US Equity | CALS IN Equity | CTP IN Equity |
| CWYR US Equity | GPOR US Equity | CNEP US Equity | LPIH US Equity | 1555 HK Equity | AJQ AU Equity |
| KEY CN Equity | PEN CN Equity | WRESQ US Equity | AGZ CN Equity | COSCO PM Equity | ONC PW Equity |
| SWN US Equity | PRHR US Equity | QEP US Equity | DENR US Equity | AEX LN Equity | GAS VN Equity |
| KSTR US Equity | EGY US Equity | WLL US Equity | PMT CN Equity | DCORP TB Equity | NGPR IN Equity |
| TSO US Equity | AAV CN Equity | OEDVQ US Equity | OCTX US Equity | BSC PM Equity | GMB MK Equity |
| TPL CN Equity | CHK US Equity | SARA US Equity | HAWKQ US Equity | HZN AU Equity | ELA LN Equity |
| TVOC US Equity | NGT US Equity | WTI US Equity | AMCF US Equity | CUE AU Equity | CRWN SS Equity |
| DLOV US Equity | MVT CN Equity | AMZGQ US Equity | PSK CN Equity | PCI ID Equity | GTLC RM Equity |
| CANRQ US Equity | BLZE US Equity | BBG US Equity | LSTMF US Equity | LLUB SL Equity | 2178 HK Equity |
| VII CN Equity | CWEI US Equity | BPZRQ US Equity | CPI CN Equity | 5009 JP Equity | TOU AU Equity |
| ECA CN Equity | SPE CN Equity | RSO CN Equity | CVE CN Equity | 8132 JP Equity | SWE AU Equity |
| APC US Equity | RCKE US Equity | TPLM US Equity | CIE US Equity | LKO AU Equity | LEK LN Equity |
| SXCL US Equity | SGY CN Equity | ZN US Equity | OAS US Equity | NRL PA Equity | MYN/GB PZ Equity |
| EGL CN Equity | ROYL US Equity | GLP US Equity | JCO CN Equity | AVNRL IT Equity | KRIS SP Equity |
| SUN CN Equity | BTE CN Equity | ALJ US Equity | ARX CN Equity | HLDSL IT Equity | REXI SP Equity |
| JOY CN Equity | AEC CN Equity | BSPE US Equity | ERN US Equity | JOEL IT Equity | IOG LN Equity |
| AIPN US Equity | NFX US Equity | GTE US Equity | EOX CN Equity | NFTA IT Equity | SNG RO Equity |
| XCLT US Equity | TRRU US Equity | LINEQ US Equity | ENSV US Equity | EQTL IT Equity | RLE AU Equity |
| KLY US Equity | LNG AU Equity | GLFE US Equity | TRGP US Equity | MEDC IJ Equity | PETR AR Equity |
| MSHFQ US Equity | DWOG US Equity | WNR US Equity | TEXS US Equity | MARI PA Equity | HUR LN Equity |
| PXD US Equity | VS CN Equity | LGCY US Equity | ASENQ US Equity | MPO AU Equity | MPHC QD Equity |
| VENX US Equity | TGL CN Equity | DK US Equity | TRCH US Equity | OSH AU Equity | SEPL LN Equity |

| | | | | |
|---|---|---|---|---|
| CHGZ RM Equity | COE AU Equity | AFR LN Equity | MISE SS Equity | AOW AU Equity |
| MFGS RM Equity | NGY AU Equity | FRR LN Equity | 096770 KS Equity | SAVP LN Equity |
| ATRL PA Equity | NXS AU Equity | GPX LN Equity | TAURB SS Equity | WEL AU Equity |
| VJGZ RM Equity | NDO AU Equity | SEA AU Equity | PETR SS Equity | UIL AU Equity |
| RIL IN Equity | MUS AU Equity | BPC LN Equity | NOR NO Equity | RAKP NO Equity |
| SIA LN Equity | 88E AU Equity | BOR LN Equity | BOE AU Equity | 2686 HK Equity |
| SEY LN Equity | SUR AU Equity | RELAPAC1 PE Equity | MPLE LN Equity | ABI SS Equity |
| NOP LN Equity | PCL AU Equity | BYE AU Equity | OIL PW Equity | MNPZ RM Equity |
| AMER LN Equity | RRS AU Equity | HDY LN Equity | RMP AU Equity | GLRP US Equity |
| SUSCO TB Equity | LGO AU Equity | ELK AU Equity | SSTAR SP Equity | DVN US Equity |
| ONGC IN Equity | FZR AU Equity | SOU LN Equity | TWO IN Equity | CNQ CN Equity |
| 76 HK Equity | LIO AU Equity | UEN LN Equity | APCL NO Equity | CPE US Equity |
| 135 HK Equity | EGO AU Equity | IGAS LN Equity | BCC AU Equity | VLO US Equity |
| PTOFS TI Equity | ICN AU Equity | NVTK RM Equity | XEL LN Equity | |
| PSA AU Equity | BANE RM Equity | RKH LN Equity | CEL AU Equity | |
| OV PM Equity | OGY AU Equity | TETY SS Equity | PRL AU Equity | |
| PTTEP TB Equity | 8011 HK Equity | RAW AU Equity | PETRO SS Equity | |
| 8097 JP Equity | 1102 HK Equity | CDS LN Equity | AOK AU Equity | |
| 5008 JP Equity | 346 HK Equity | AMOC EY Equity | PETROR AB Equity | |
| 467 HK Equity | SUGI IJ Equity | SCORE NO Equity | GGL AU Equity | |
| PHEN PM Equity | RPT LN Equity | MXP LN Equity | NGE AU Equity | |
| TLW LN Equity | GED LN Equity | GAZ MC Equity | IKARUS KK Equity | |
| 014530 KS Equity | FPM LN Equity | TNP AU Equity | MATD LN Equity | |
| HOE IN Equity | ITRR SP Equity | PTTGC TB Equity | ESSO TB Equity | |
| TUPRS TI Equity | OEX AU Equity | MXO LN Equity | IOF LN Equity | |
| AZZ AU Equity | JPR AU Equity | SARCO AB Equity | UNPZ RU Equity | |
| MNPZ RM Equity | 6505 TT Equity | TEG AU Equity | CHAR LN Equity | |
| PECB PM Equity | UFNC RU Equity | EME LN Equity | SGP TB Equity | |
| IOCL IN Equity | 000554 CH Equity | IOX NO Equity | INDI LN Equity | |
| 933 HK Equity | COI AU Equity | ISRAL IT Equity | OGXP3 BZ Equity | |
| YUKO RU Equity | TSV AU Equity | LAPD IT Equity | CAD LN Equity | |
| TAP AU Equity | 600387 CH Equity | CTP AU Equity | TMK AU Equity | |
| SAM MC Equity | ENRG IJ Equity | AKERBP NO Equity | BRU AU Equity | |
| NEN AU Equity | OGDC PA Equity | 038500 KS Equity | MOIL EY Equity | |
| PPP AU Equity | SXT IN Equity | PANR LN Equity | CONF IN Equity | |
| 553810Q FH Equity | AEN LN Equity | CASO SS Equity | AOS IN Equity | |
| BCP TB Equity | BOIL LN Equity | GEEC LN Equity | SLE LN Equity | |
| OPM PM Equity | PPC LN Equity | INK AU Equity | GPPE IN Equity | |
| COPEC CI Equity | MENR SP Equity | ENERGYH KK Equity | PVG VN Equity | |
| RAF RO Equity | BYCO PA Equity | PSUR AR Equity | 852 HK Equity | |
| DNO NO Equity | VOG LN Equity | LNC SP Equity | PGC VN Equity | |
| PRL PA Equity | TOP TB Equity | SAS AU Equity | MCLAIRB SS Equity | |
| POL PA Equity | PERC PM Equity | SRS IM Equity | PGS VN Equity | |
| 010950 KS Equity | 1605 JP Equity | KRKN RM Equity | PLC VN Equity | |
| 7441 JP Equity | LNG AU Equity | AKK AU Equity | BPL PA Equity | |
| PMG LN Equity | KAR AU Equity | APY AU Equity | NFEXL IT Equity | |
| BSO AU Equity | MOG AU Equity | PTR ID Equity | GERL IN Equity | |
| AWE AU Equity | KTE AU Equity | 5019 JP Equity | OINL IN Equity | |
| 702 HK Equity | STX AU Equity | 4O1 BU Equity | SEH AU Equity | |
| DEDRL IT Equity | BLVN LN Equity | OUHUA SP Equity | OXX AU Equity | |
| DLEN IT Equity | COP LN Equity | PPHN SW Equity | EXI LN Equity | |
| PRP ID Equity | EOG LN Equity | PZOL IT Equity | GIVOL IT Equity | |
| EMR AU Equity | SRSP LN Equity | TMAN LN Equity | LPHLL IT Equity | |
| LNR AU Equity | GKP LN Equity | CAIR IN Equity | NORTH NO Equity | |
| LUPE SS Equity | MEL AU Equity | GAS LN Equity | ALGS IT Equity | |
| CVN AU Equity | RRC RO Equity | ORL IT Equity | BIPI IJ Equity | |
| BUL AU Equity | PELE LN Equity | ACY GR Equity | KEA LN Equity | |
| PTT TB Equity | OEL AU Equity | HAIK LN Equity | SHELB SS Equity | |
| MKE AU Equity | JNOS RM Equity | HAWK LN Equity | ENQ LN Equity | |
| CAO SP Equity | RPMG3 BZ Equity | LGO LN Equity | BRIDGE NO Equity | |
| NEC NO Equity | GOP AU Equity | SFC VN Equity | PEN NO Equity | |
| MOH GA Equity | PPL PA Equity | SOLO LN Equity | 128820 KS Equity | |
| 600256 CH Equity | 600157 CH Equity | VGAS LN Equity | ARG LN Equity | |
| 000817 CH Equity | EDR LN Equity | RXP LN Equity | RATIL IT Equity | |
| PAR SS Equity | QFI LN Equity | DOME SS Equity | FDM AU Equity | |
| BUY AU Equity | TRP LN Equity | UEP LN Equity | ITP IN Equity | |
| CPN AU Equity | LHD LN Equity | ATLA DC Equity | | |

## APPENDIX 7.4 – DRY BULK SAMPLE AFTER BLOOMBERG SCREENING AND COMPUSTAT (COMPANY NAMES)

B&H OCEAN CARRIERS LTD
PANGAEA LOGISTICS SOLUTIONS
GOLDEN OCEAN GROUP
EXCEL MARITIME CARRIERS LTD
SHIP FINANCE INTL LTD
DRYSHIPS INC
DIANA SHIPPING INC
EAGLE BULK SHIPPING INC
QUINTANA MARITIME LTD
GENCO SHIPPING & TRADING
NEWLEAD HOLDINGS LTD
STAR BULK CARRIERS CORP
FREESEAS INC
EUROSEAS LTD
ULTRAPETROL BAHAMAS LTD
RAND LOGISTICS INC
OCEANFREIGHT INC
PARAGON SHIPPING INC
SINOPEC WUHAN PHOENIX CO LTD
U SEA BULK SHIPPING AS
PACIFIC BASIN SHIPPING LTD
WILSON ASA
ARPENI PRATAMA OCEAN LINE
COSCO SHIPPING HLDGS CO LTD
COURAGE MARINE GROUP LTD
RICHFIELD INTERNATIONAL LTD
SEANERGY MARITIME HLDGS CORP
NAVIOS MARITIME PARTNERS LP
SAFE BULKERS INC
BRITANNIA BULK HOLDINGS INC
BALTIC TRADING LTD
ALMA MARITIME LTD -REDH
GLOBUS MARITIME LTD
SCORPIO BULKERS
CMB-CIE MARITIME BELGE NV/SA
LEIF HOEGH & CO ASA
FARSTAD SHIPPING ASA
CHOWGULE STEAMSHIP
VARUN SHIPPING
BULK INVEST ASA
SHIPPING CORP OF INDIA LTD
GOLDENPORT HLDGS INC
SINOTRANS SHIPPING LTD
HELLENIC CARRIERS LTD
GREAT HARVEST MAETA GRP HLGD
TRANSPORTATION & TRADE SRVC
KDM SHIPPING PUBLIC LTD

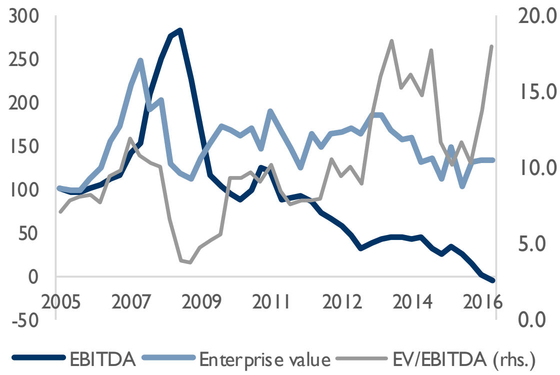
## APPENDIX 7.5 – EXAMPLE OF BETA EXTRACTION BLOOMBERG



# APPENDIX 8 INDUSTRY LEVEL ANALYSIS ACROSS TIME

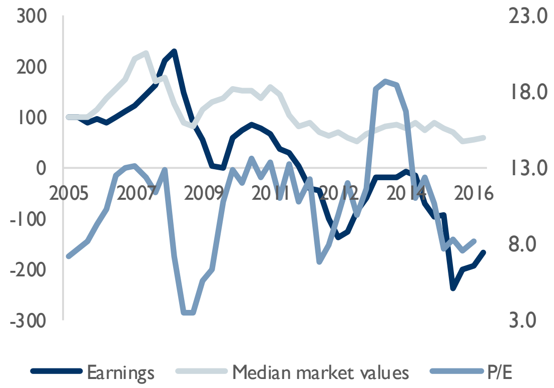
## APPENDIX 8.1 DRY BULK

**Dry bulk - EV/EBITDA on indexed factors**



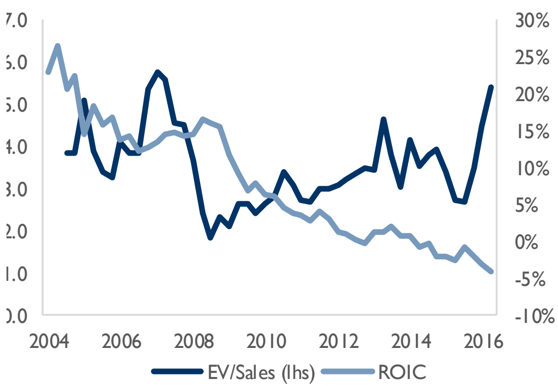

Source: Compustat and Bloomberg

**Dry bulk - P/E on indexed factors**



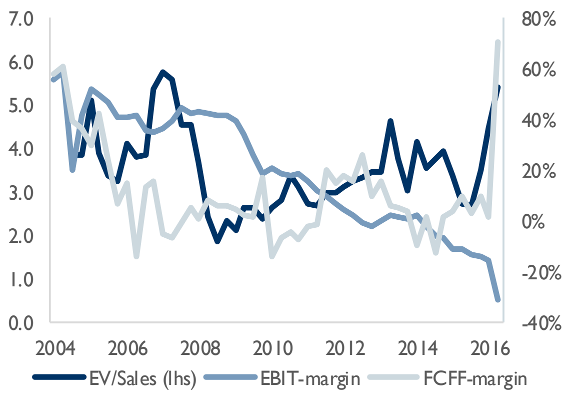

Source: Compustat and Bloomberg

**Dry Bulk - EV/Sales & ROIC**



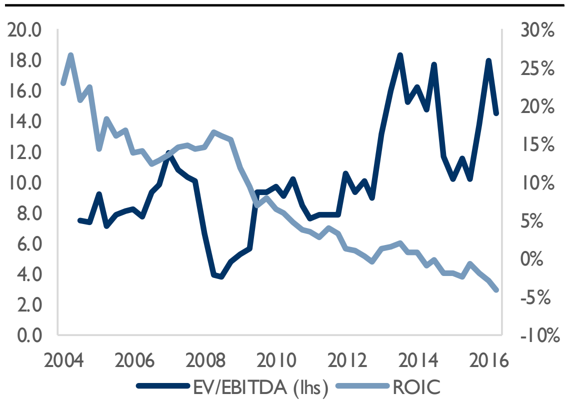

Source: Compustat and Bloomberg

**Dry Bulk - EV/Sales & margins**



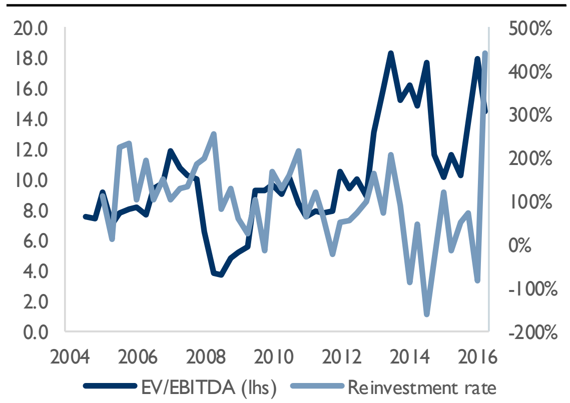

Source: Compustat and Bloomberg

**Dry Bulk - EV/EBITDA on ROIC**



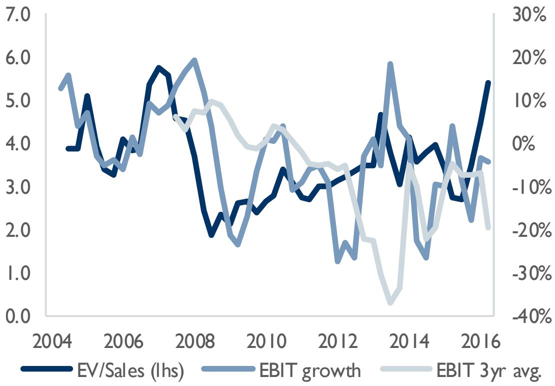

Source: Compustat and Bloomberg

**Dry Bulk - EV/EBITDA on Reinvestmentrate**



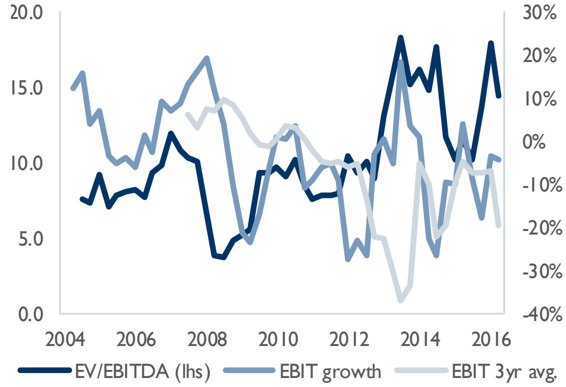

Source: Compustat and Bloomberg

**Dry bulk - EV/Sales & EBIT growth**




Source: Compustat and Bloomberg

**Dry bulk - EV/EBITDA & EBIT growth**

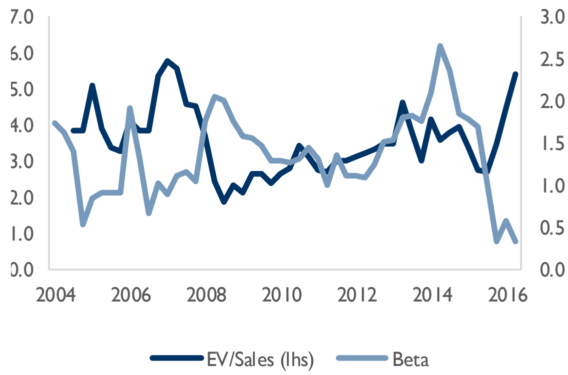



Source: Compustat and Bloomberg

**Dry bulk - P/B on beta**

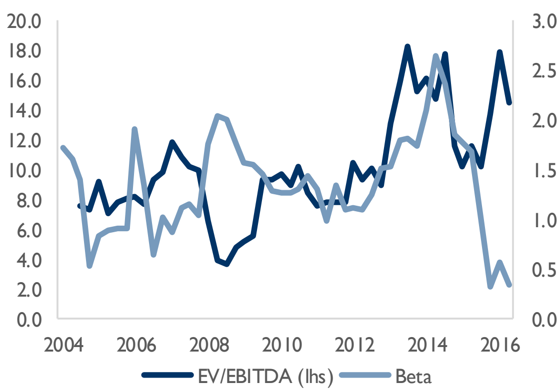

Source: Compustat and Bloomberg

**Dry bulk - EV/Sales on Beta**



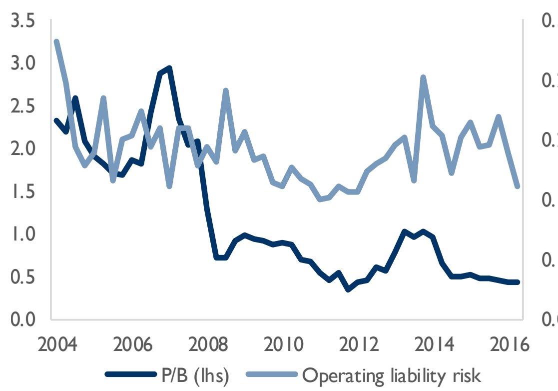

Source: Compustat and Bloomberg

**Dry bulk - EV/EBITDA on beta**



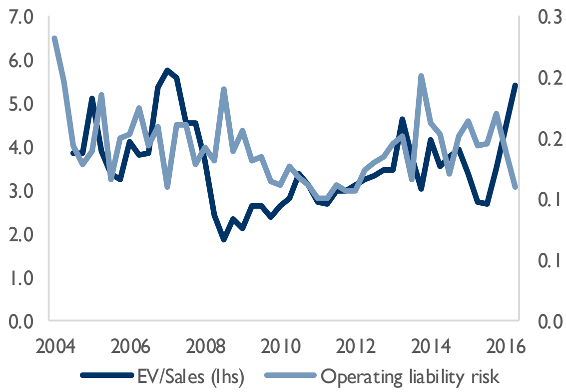

Source: Compustat and Bloomberg

**Dry bulk - P/B on operating liability risk**




Source: Compustat and Bloomberg

**Dry bulk - EV/Sales on operating liability risk**

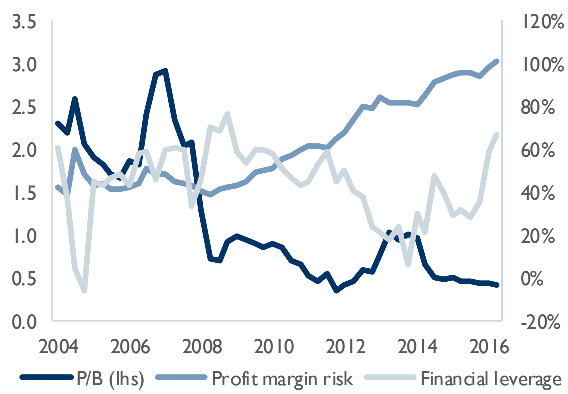



Source: Compustat and Bloomberg

**Dry bulk - EV/EBITDA on operating liability risk**


Source: Compustat and Bloomberg

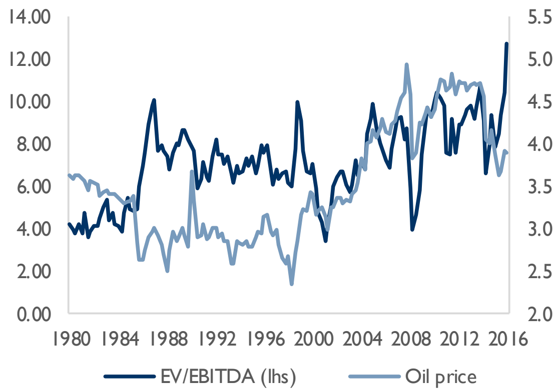
**Dry bulk - P/B on profit margin risk and leverage**




Source: Compustat and Bloomberg

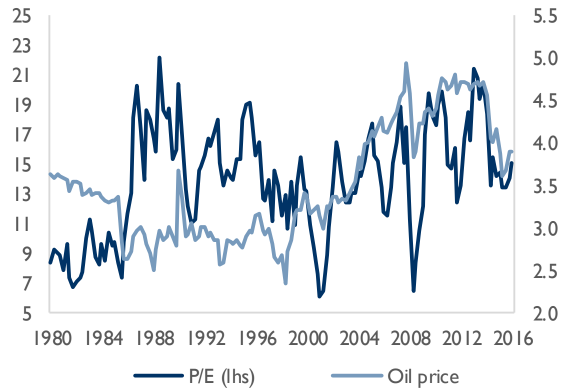
## APPENDIX 8.2 E&P

**E&P EV/EBITDA on oil price**



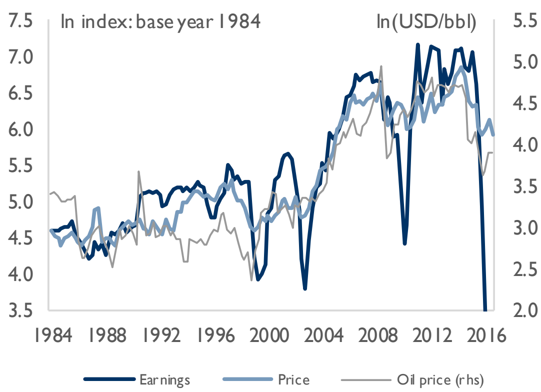

Source: Compustat and Bloomberg

**E&P - P/E on oil price**



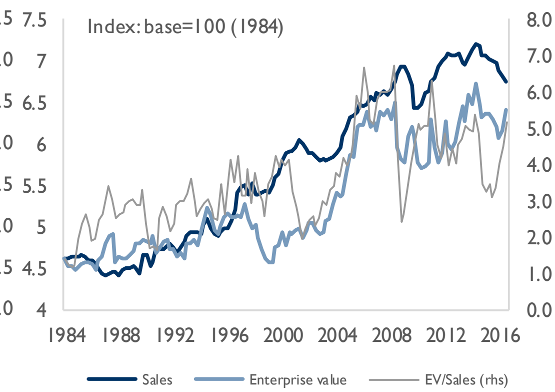

Source: Compustat and Bloomberg

**Earnings, price and oil price**



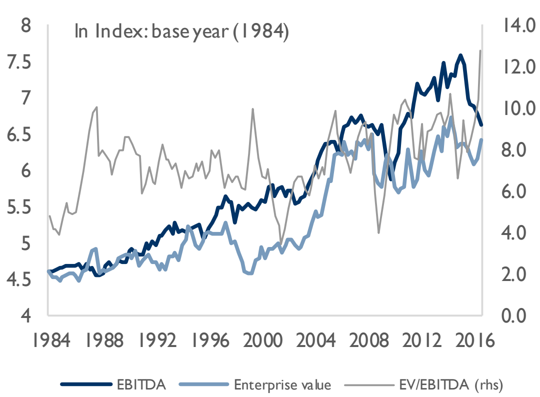

Source: Compustat and Bloomberg

**EV/Sales on indexed factors**



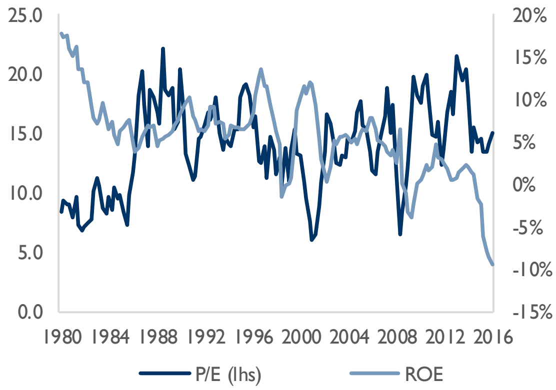

Source: Compustat and Bloomberg

**EV/EBITDA on indexed factors**



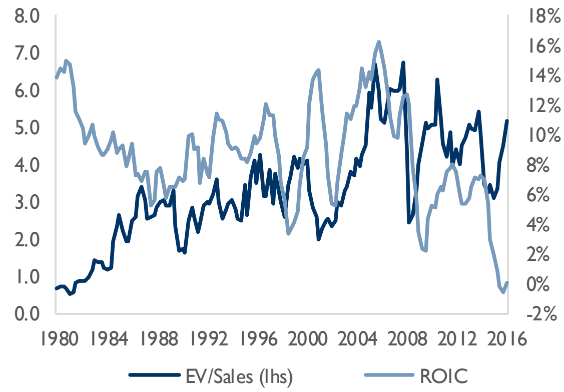

Source: Compustat and Bloomberg

**P/E on ROE**



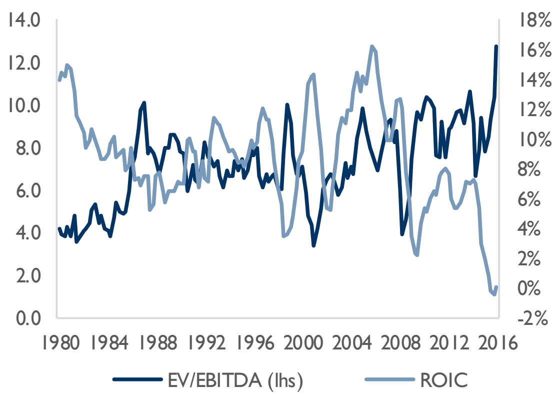

Source: Compustat and Bloomberg

**EV/Sales on ROIC**



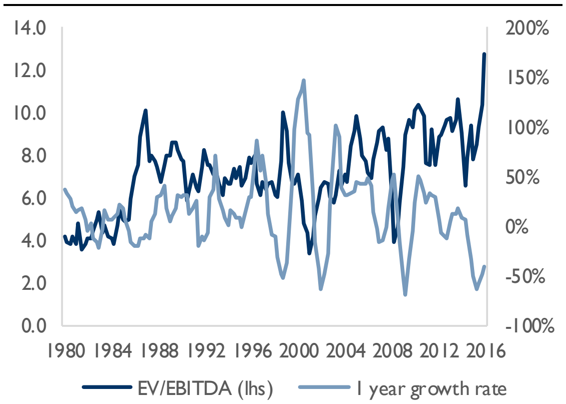

Source: Compustat and Bloomberg

**EV/EBITDA on ROIC**



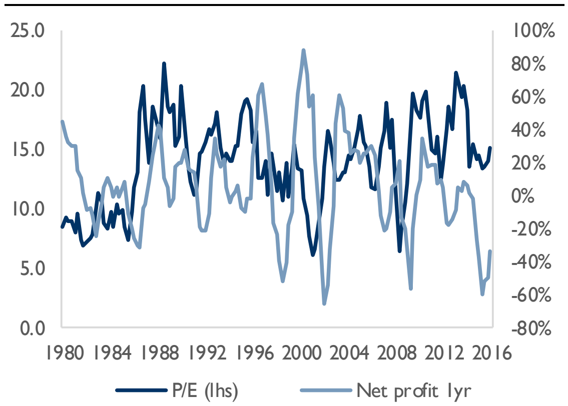

Source: Compustat and Bloomberg

**EV/EBITDA on NOPAT growth**



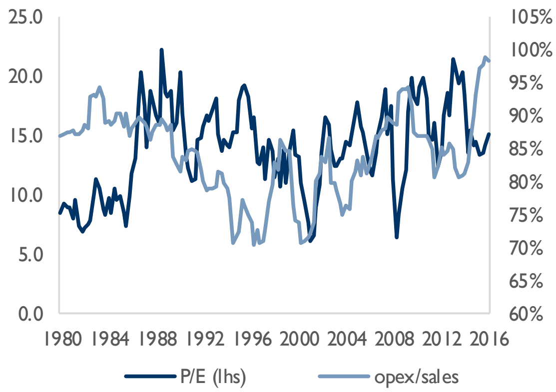

Source: Compustat and Bloomberg

**P/E on Net profit growth**



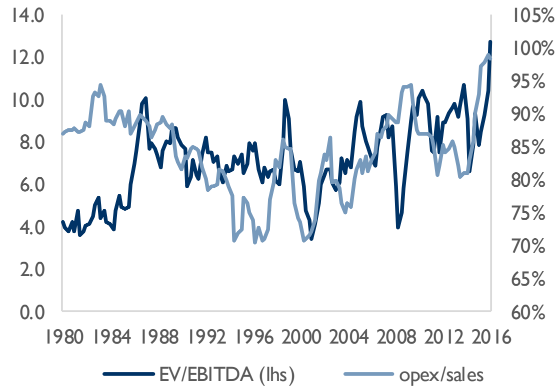

Source: Compustat and Bloomberg

**P/E on profit margin risk**



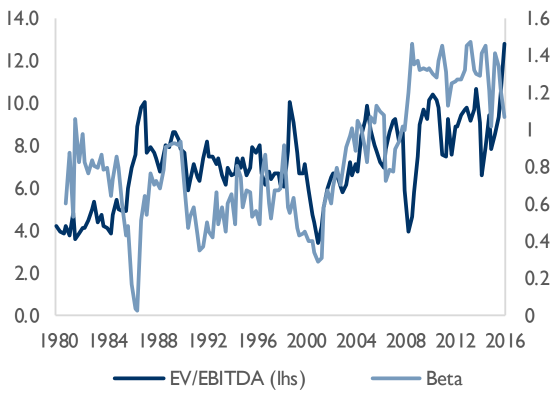

Source: Compustat and Bloomberg

**EV/EBITDA on profit margin risk**



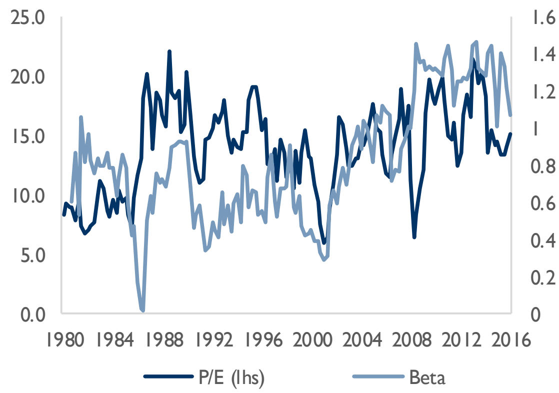

Source: Compustat and Bloomberg

**EV/EBITDA on Beta**



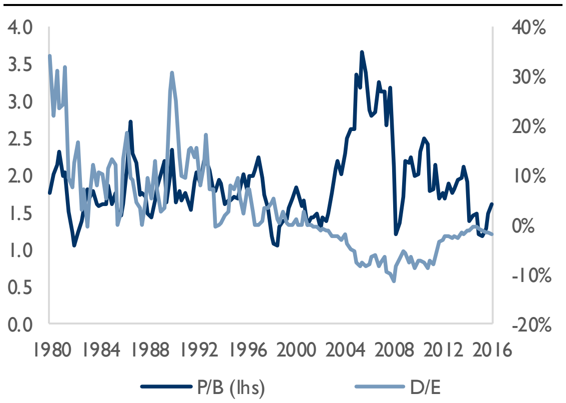

Source: Compustat and Bloomberg

**P/E on Beta**



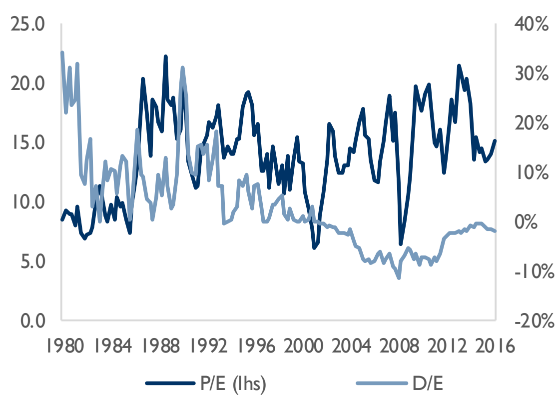

Source: Compustat and Bloomberg

**P/B on Debt/Equity**



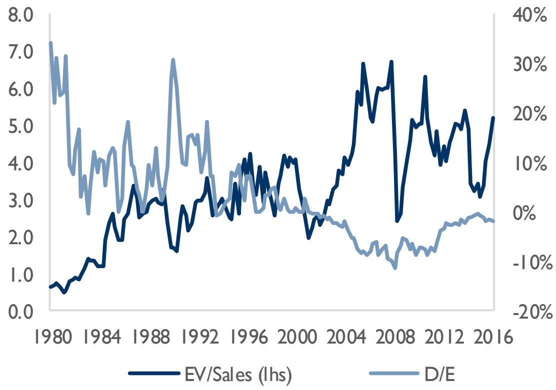

Source: Compustat and Bloomberg

**P/E on Debt/Equity**



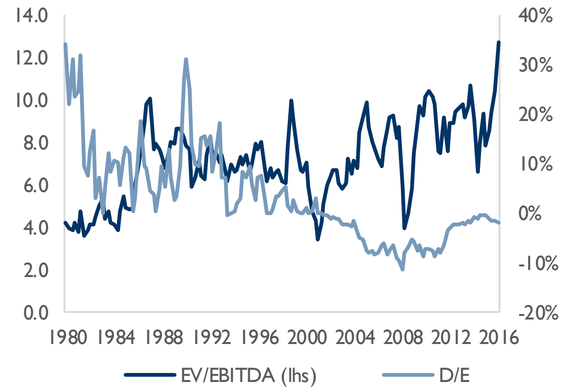

Source: Compustat and Bloomberg

**EV/Sales on Debt/Equity**



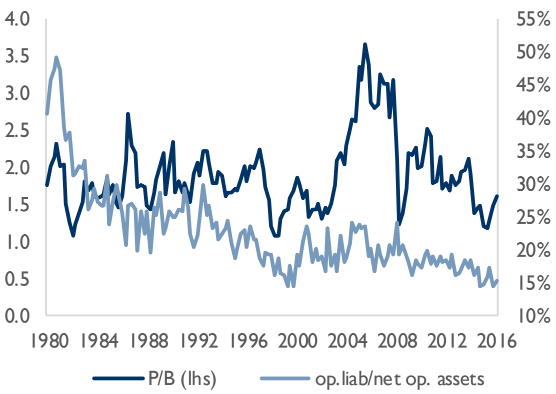

Source: Compustat and Bloomberg

**EV/EBITDA on Debt/Equity**



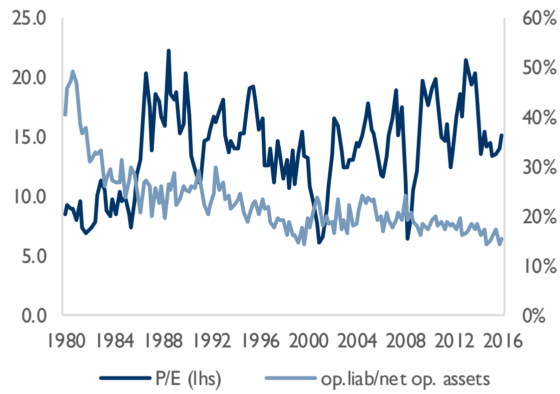

Source: Compustat and Bloomberg

**P/B on operating liability risk**



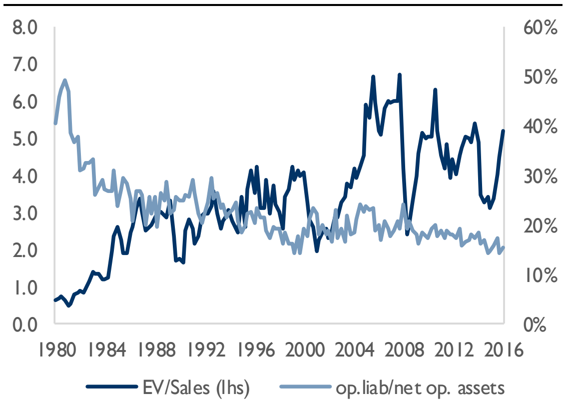

Source: Compustat and Bloomberg

**P/E on operating liability risk**



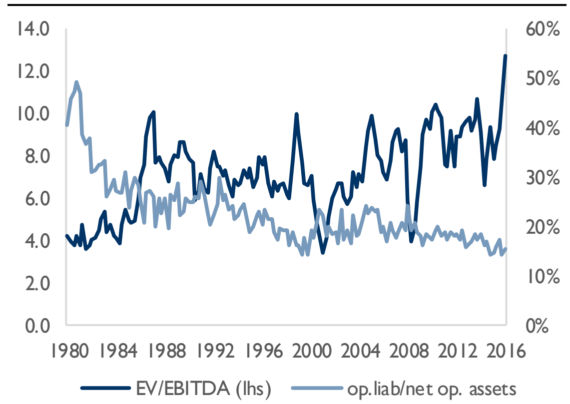

Source: Compustat and Bloomberg

**EV/Sales on operating liability risk**




Source: Compustat and Bloomberg

**EV/EBITDA on operating liability risk**

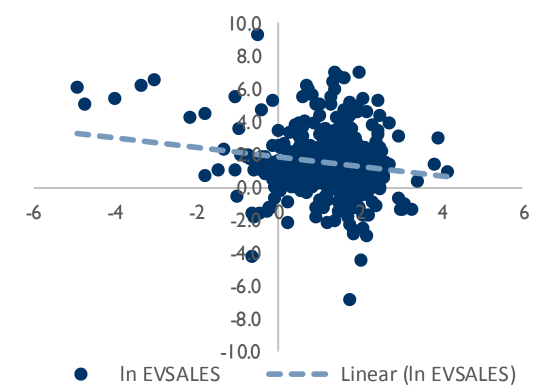



Source: Compustat and Bloomberg

# APPENDIX 9 REGRESSION ANALYSIS

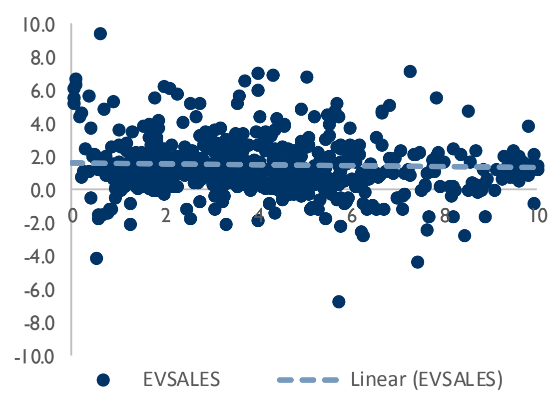
## APPENDIX 9.1 MODEL SPECIFICATIONS AND ASSUMPTIONS

**ln EV/Sales on Beta**



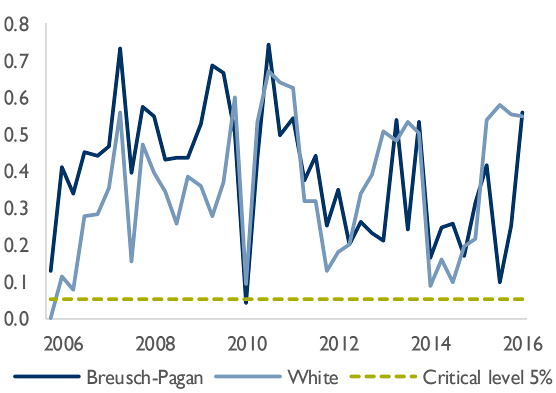

Source: Own creation

**EV/Sales on Beta**



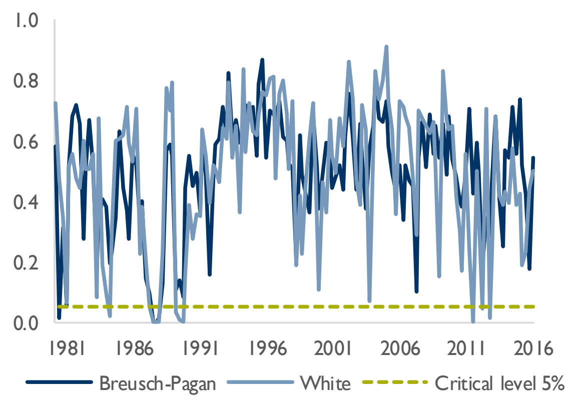

Source: Own creation

**BP and White on PB Dry Bulk**



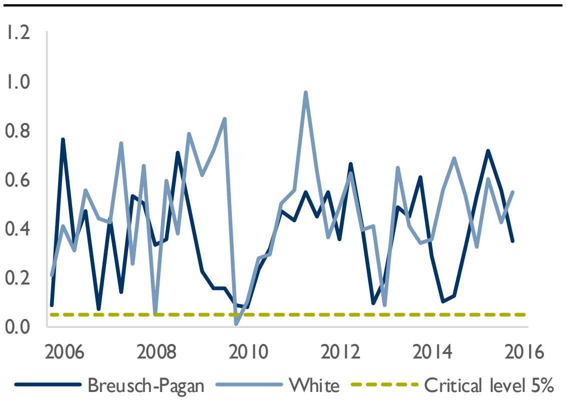

Source: Own creation

**BP and White on PB E&P**



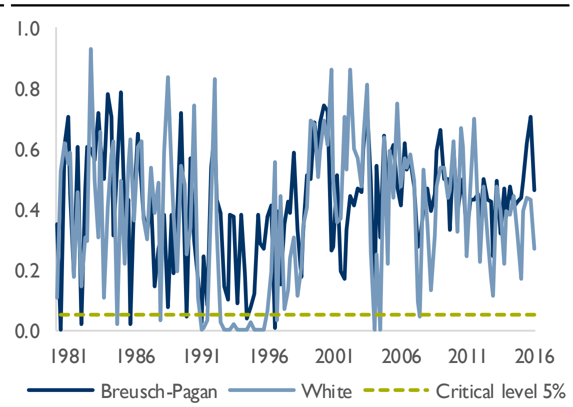

Source: Own creation

**BP and White on EVEBITDA Dry Bulk**



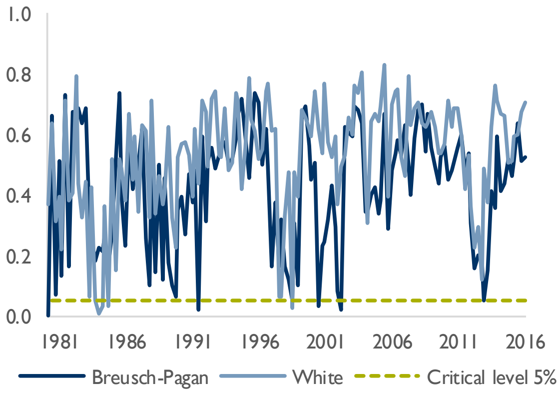

Source: Own creation

**BP and White on EVEBITDA E&P**



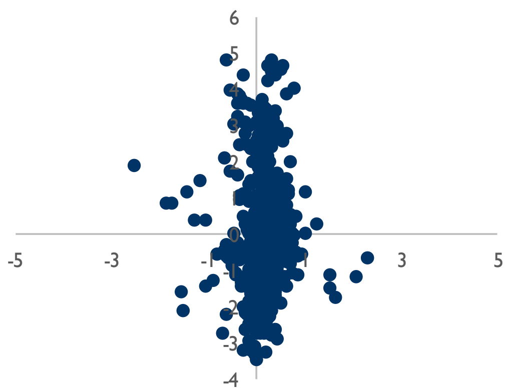

Source: Own creation

**BP and White on PE E&P**



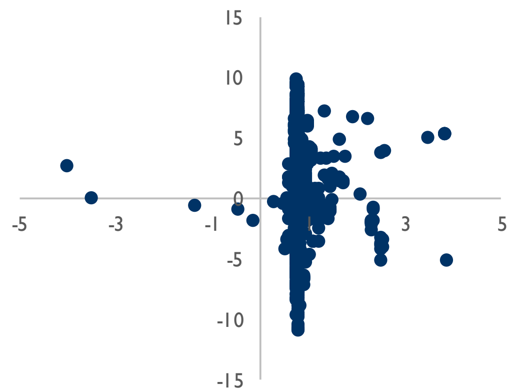

Source: Own creation

**Predicted P/B Dry Bulk on residuals**



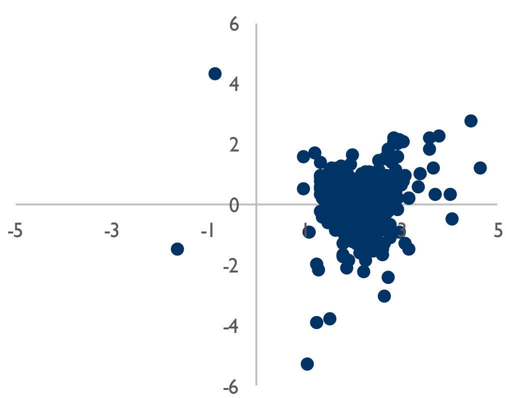

Source: Own creation

**Predicted P/B E&P on residuals**



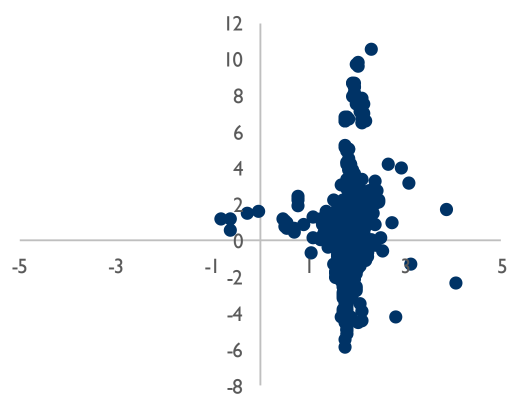

Source: Own creation

**Predicted EV/EBITDA Dry Bulk on residuals**



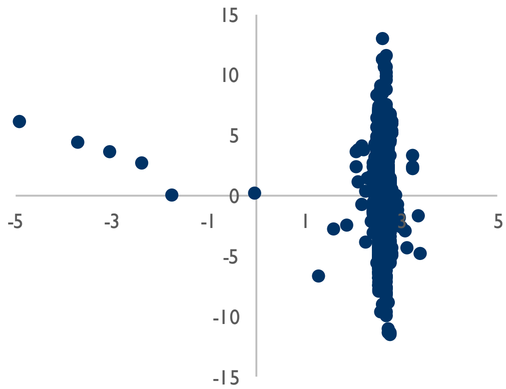

Source: Own creation

**Predicted EV/EBITDA E&P on residuals**



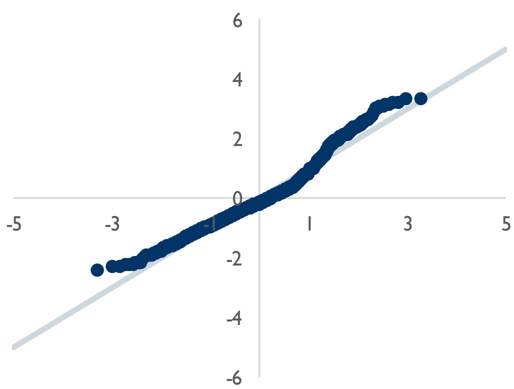

Source: Own creation

**Predicted P/E E&P on residuals**



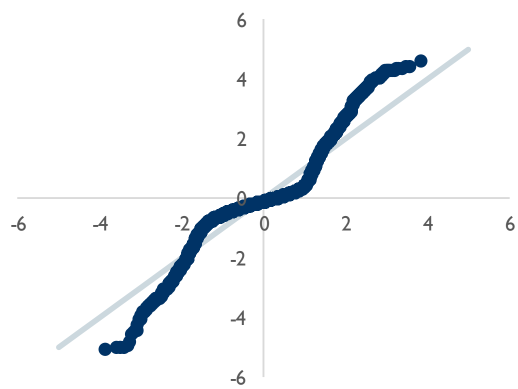

Source: Own creation

**Q-Q plot P/B Dry Bulk residuals**



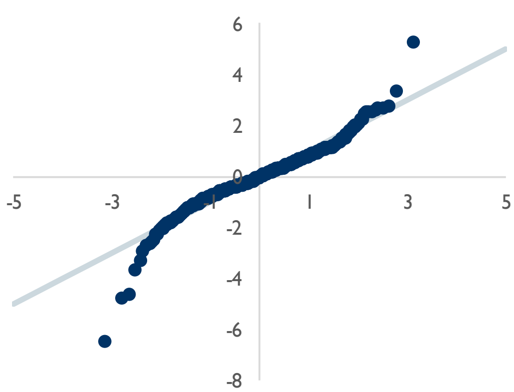

Source: Own creation

**Q-Q plot P/B E&P residuals**



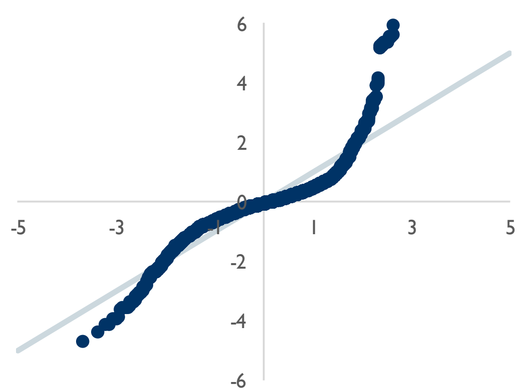

Source: Own creation

**Q-Q plot EV/EBITDA Dry Bulk residuals**



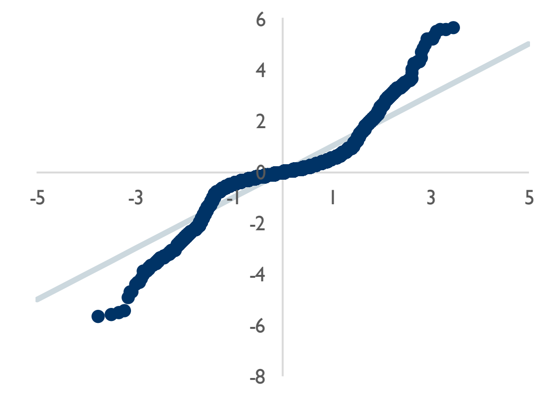

Source: Own creation

**Q-Q plot EV/EBITDA E&P residuals**



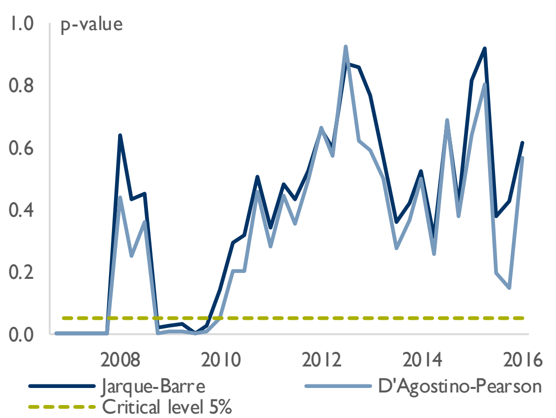

Source: Own creation

**Q-Q plot P/E E&P residuals**



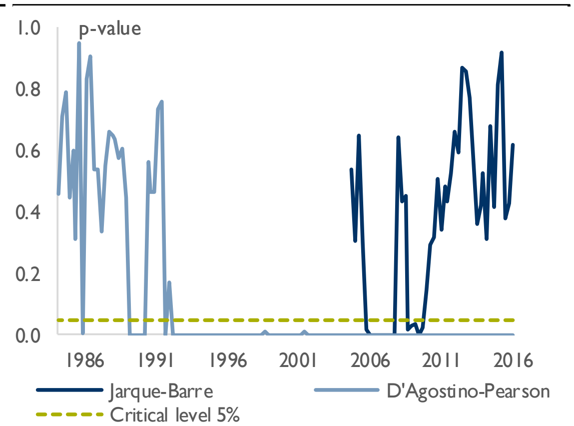

Source: Own creation

**JB and DP on ln PB Dry Bulk**



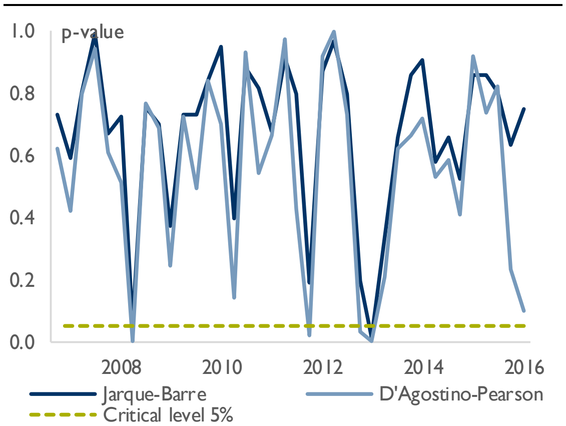

Source: Own creation

**JB and DP on ln PB E&P**



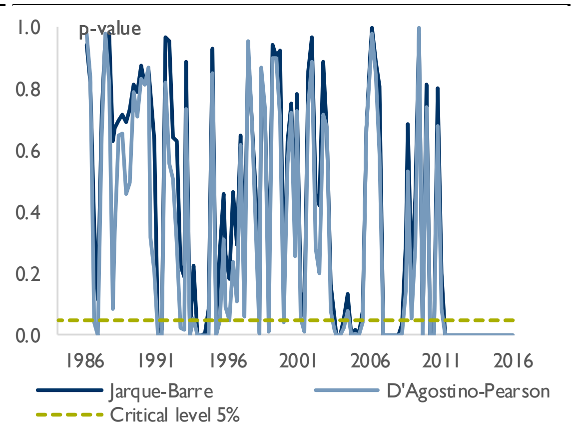

Source: Own creation

**JB and DP on ln EVEBITDA Dry Bulk**



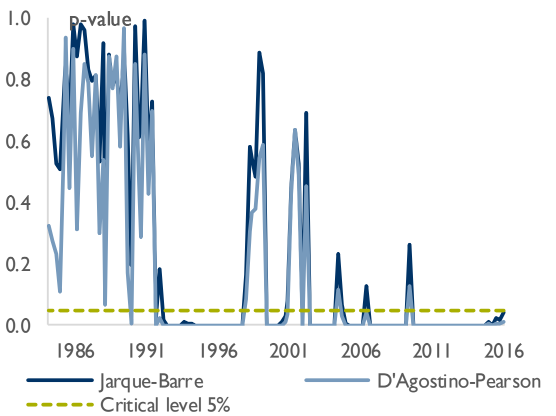

Source: Own creation

**JB and DP on ln EVEBITDA E&P**



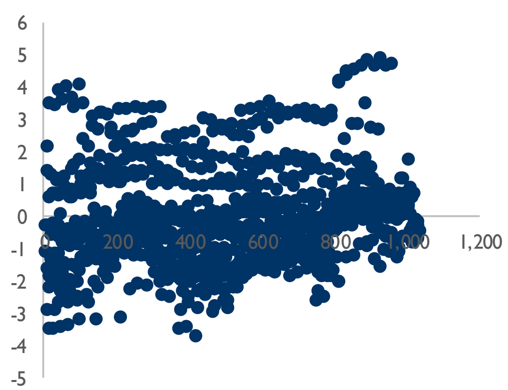

Source: Own creation

**JB and DP on ln PE E&P**



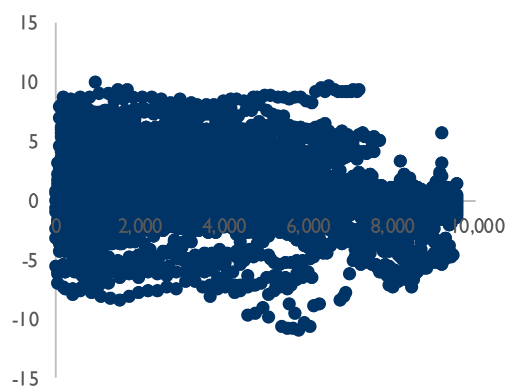

Source: Own creation

**P/B Dry Bulk residuals & row #**



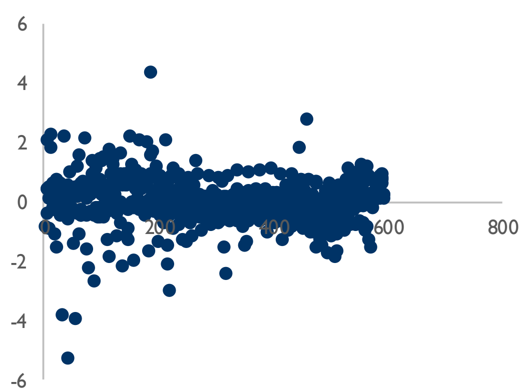

Source: Own creation

**P/B E&P residuals & row #**



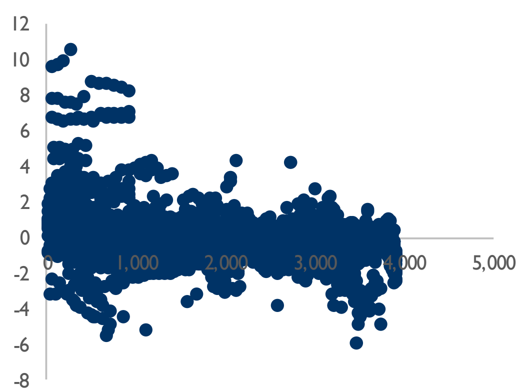

Source: Own creation

**EV/EBITDA Dry Bulk residuals & row #**




Source: Own creation

**EV/EBITDA E&P residuals & row #**



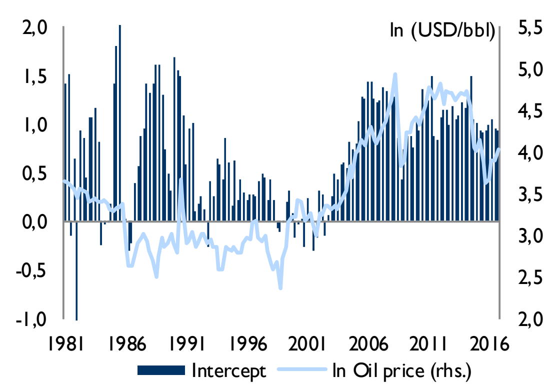

Source: Own creation

**P/E E&P residuals & row #**


Source: Own creation

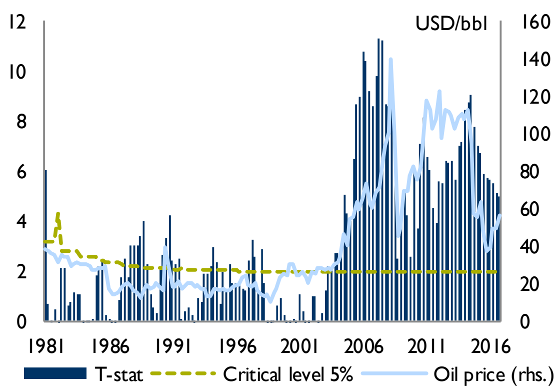
## APPENDIX 9.2 INITIAL REGRESSION RESULTS AND ANALYSIS

**E&P - Ln P/B reg. Intercept & ln oil price**



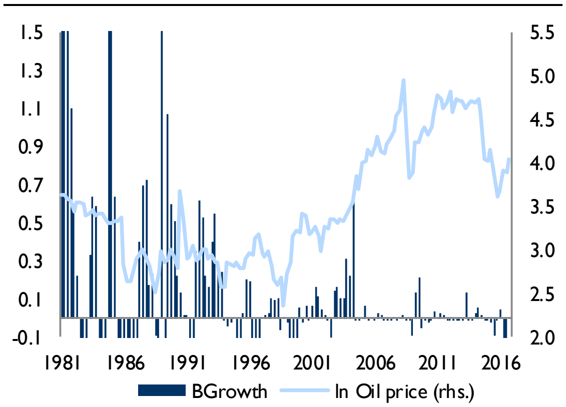

Source: Own creation

**E&P - Ln P/B reg. Intercept t-stat & oil price**



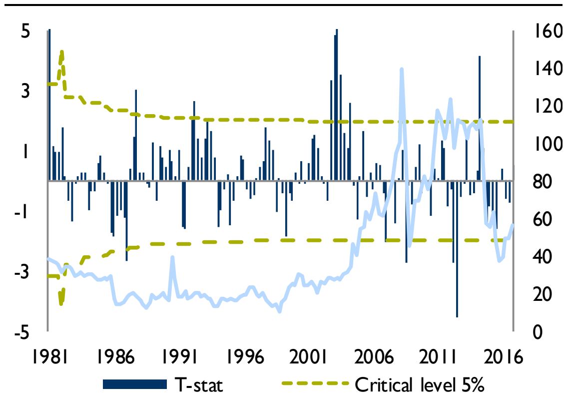

Source: Own creation

**E&P - Ln P/B reg. Bgrowth & Oil price**



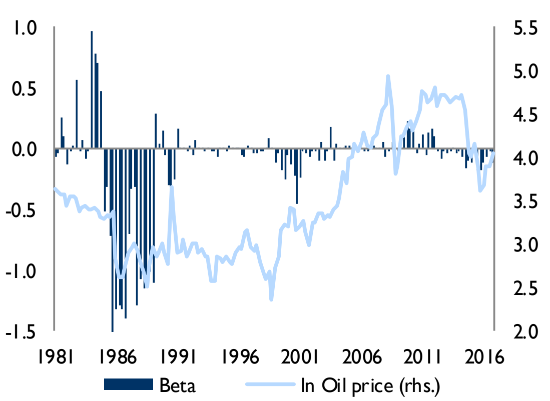

Source: Own creation

**E&P - Ln P/B reg. Bgrowth t-stat & oil price**




Source: Own creation

**E&P - Ln P/B reg. Beta & Oil price**

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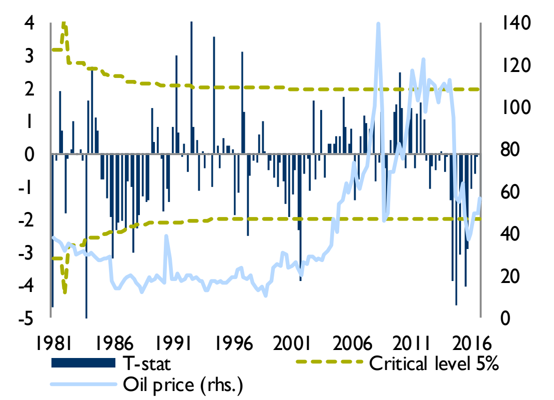
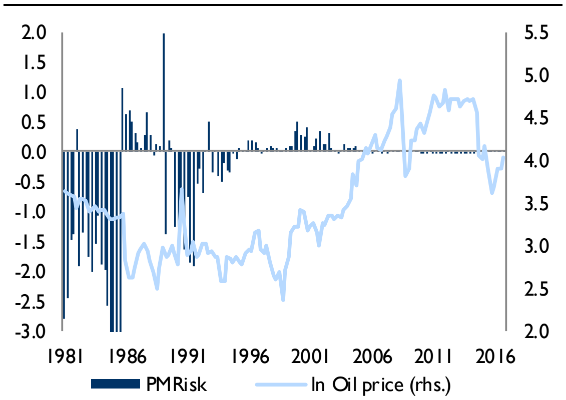
**E&P - Ln P/B reg. Beta t-stat & oil price**




Source: Own creation

**E&P - Ln P/B reg. PM risk & Ln Oil price**

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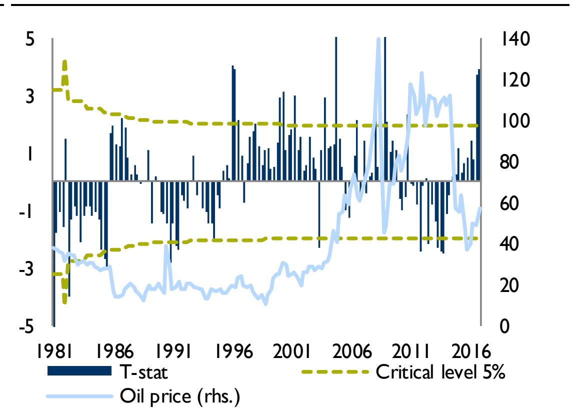


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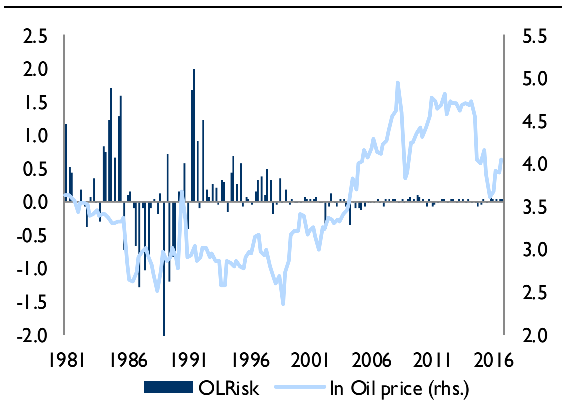


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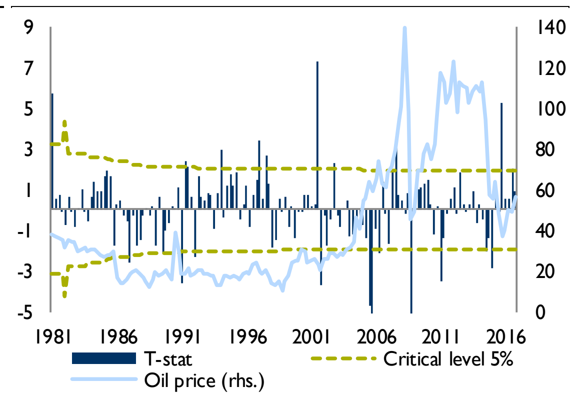
**E&P - Ln P/B reg. OL risk t-stat & oil price**

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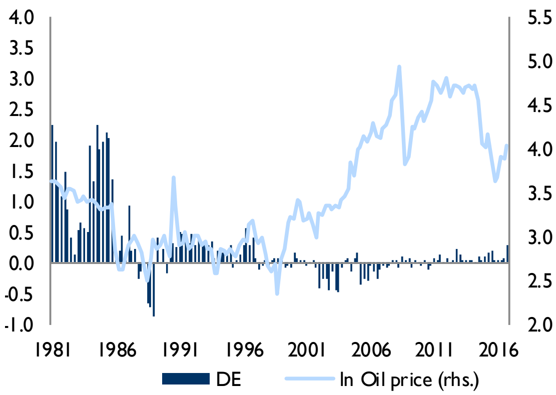
**E&P - Ln P/B reg. Debt/Equity & Ln Oil price**

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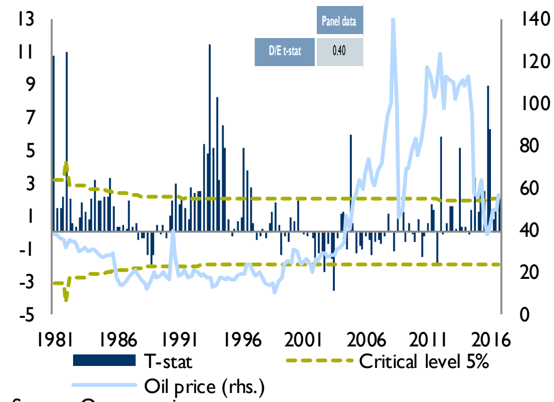
**E&P - Ln P/B reg. Debt/Equity t-stat & oil price**

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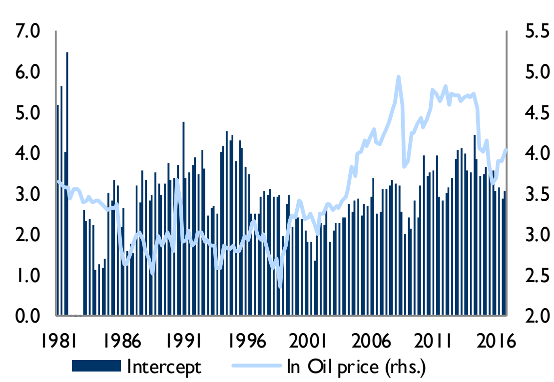
**E&P - Ln P/E reg. Intercept & ln oil price**

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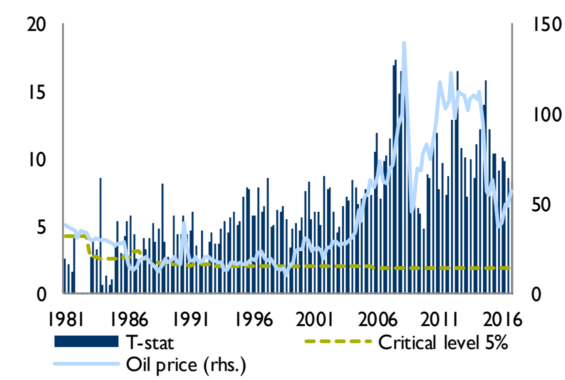
**E&P - Ln P/E reg. Intercept t-stat & oil price**

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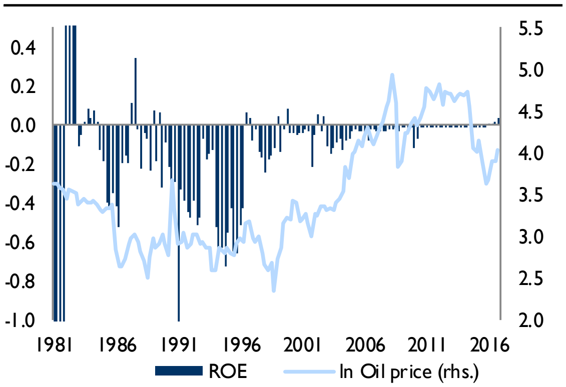
**E&P - Ln P/E reg. ROE & ln oil price**

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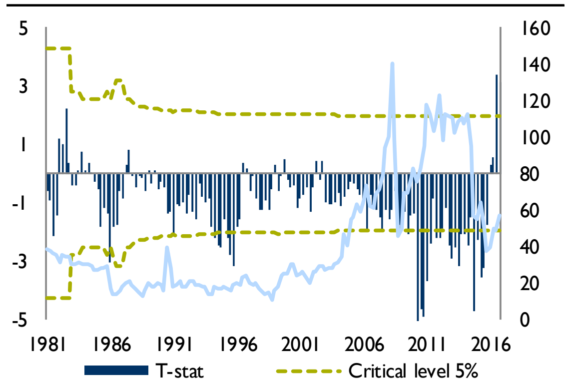
**E&P - Ln P/E reg. ROE t-stat & oil price**

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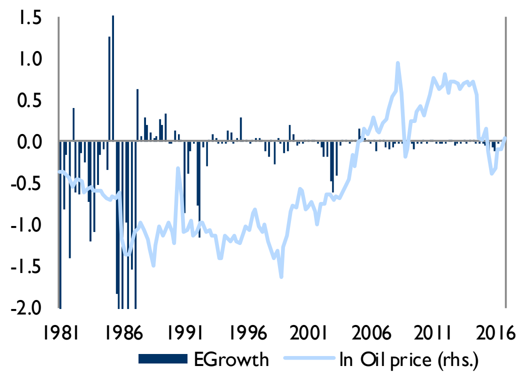
**E&P - Ln P/E reg. E growth & ln oil price**

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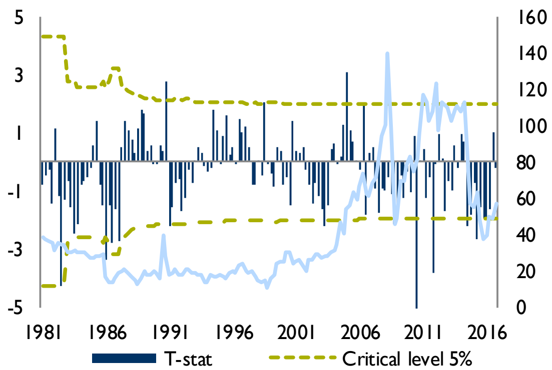
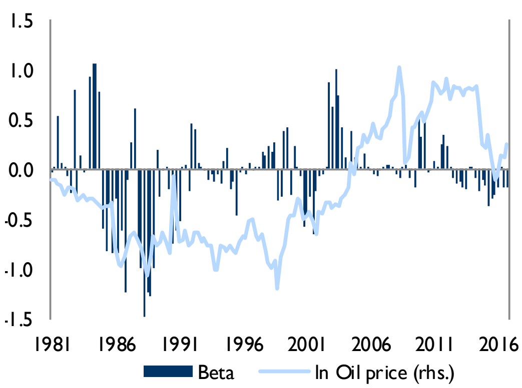
**E&P - Ln P/E reg. E growth t-stat & oil price**



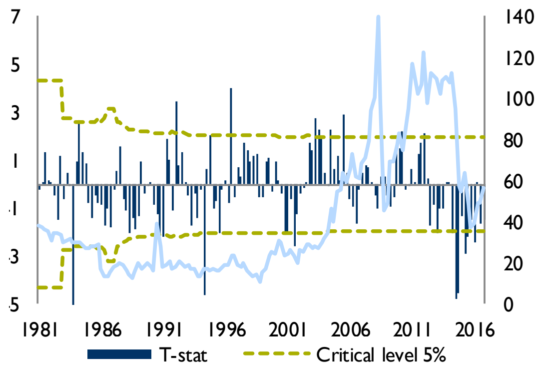

Source: Own creation

**E&P - Ln P/E reg. Beta & ln oil price**



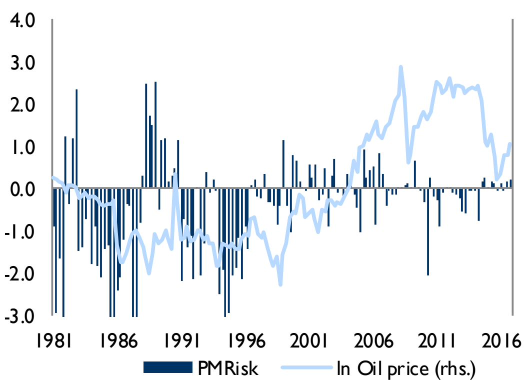

Source: Own creation

**E&P - Ln P/E reg. Beta t-stat & oil price**




Source: Own creation

**E&P - Ln P/E reg. PM risk & ln oil price**

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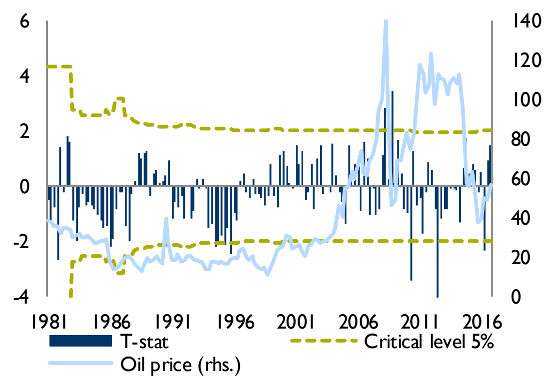
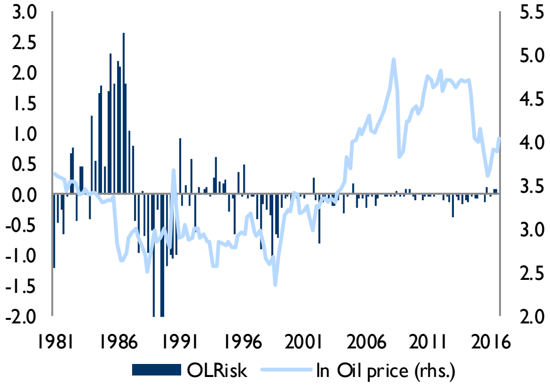
**E&P - Ln P/E reg. PM risk t-stat & oil price**




Source: Own creation

**E&P - Ln P/E reg. OL risk & ln oil price**

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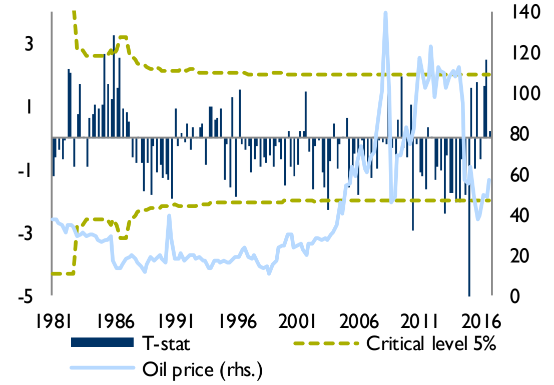
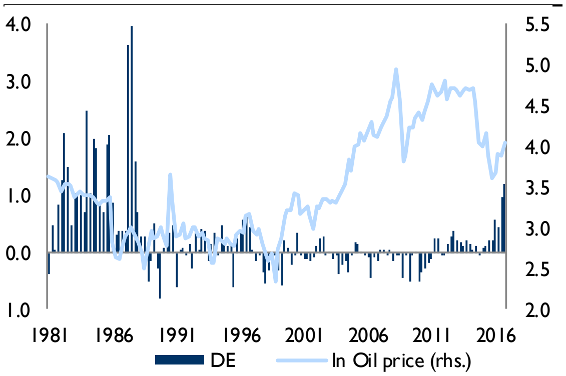
**E&P - Ln P/E reg. OL risk t-stat & oil price**



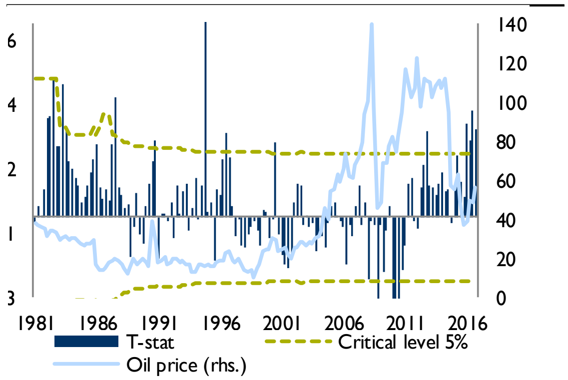

Source: Own creation

**E&P - Ln P/E reg. DE risk & ln oil price**



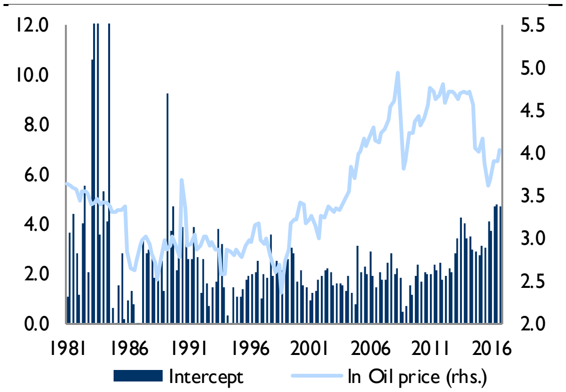

Source: Own creation

**E&P - Ln P/E reg. DE t-stat & oil price**



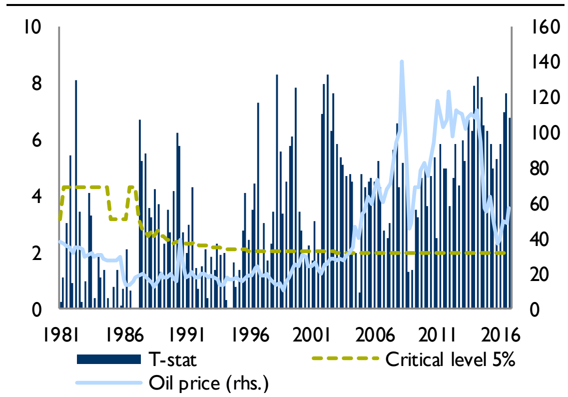

Source: Own creation

**E&P - Ln EV/EBITDA reg. Intercept & ln oil price**



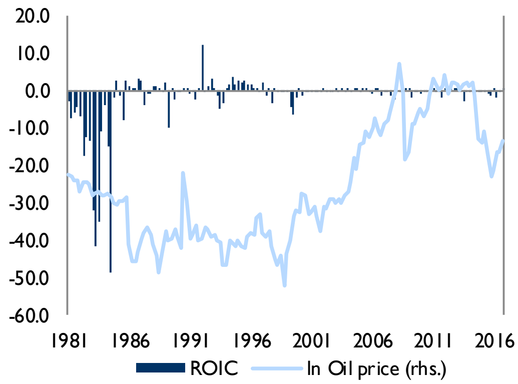

Source: Own creation

**E&P-Ln EV/EBITDA reg. Intercept t-stat & oil price**




Source: Own creation

**E&P - Ln EV/EBITDA reg. ROIC & ln oil price**

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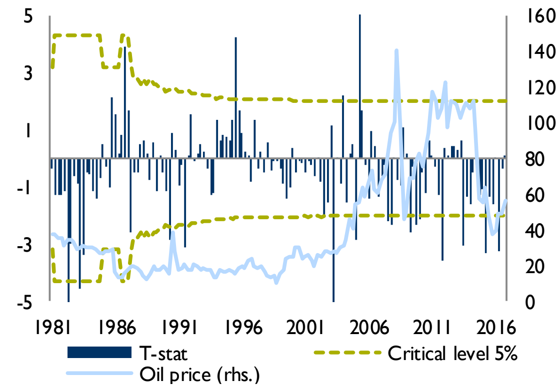
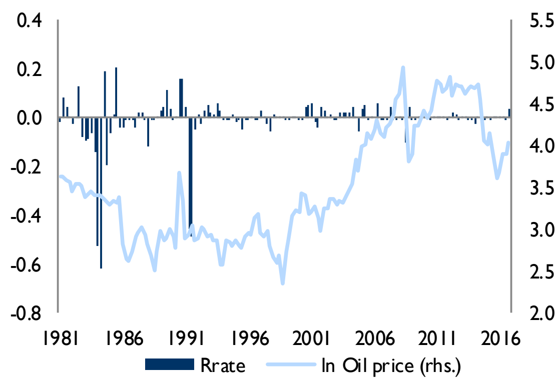
**E&P-Ln EV/EBITDA reg. ROIC t-stat & oil price**




Source: Own creation

**E&P - Ln EV/EBITDA reg. Rrate & ln oil price**

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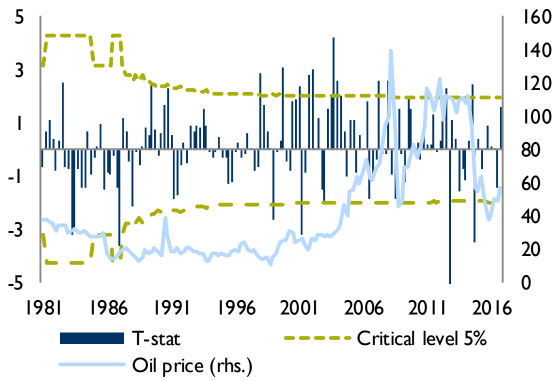
**E&P-Ln EV/EBITDA reg. Rrate t-stat & oil price**

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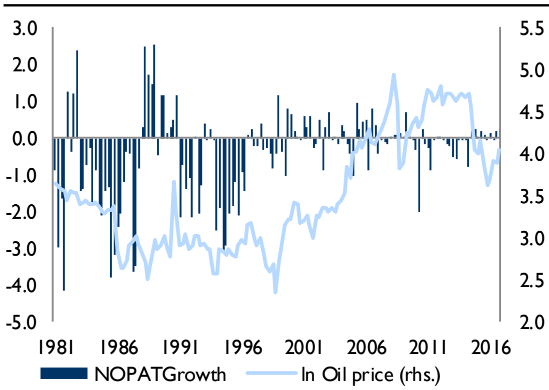
**E&P - Ln EV/EBITDA reg. NOPATg & ln oil price**

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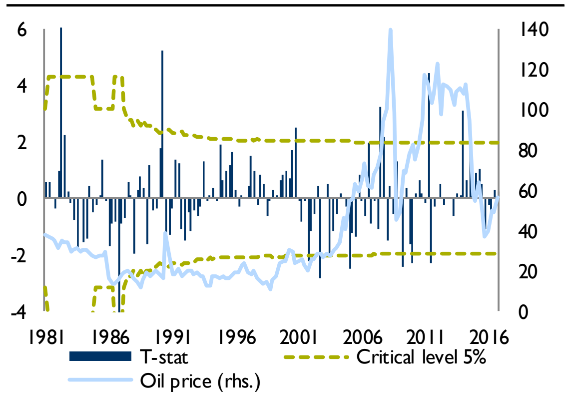


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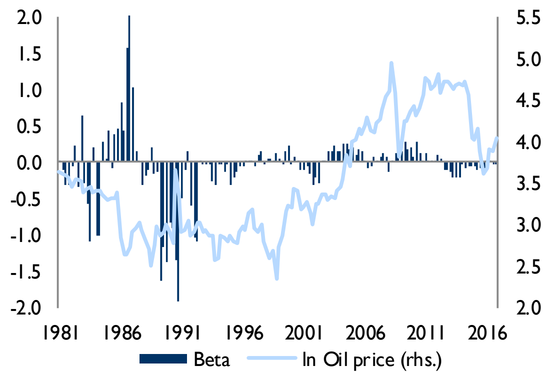
**E&P - Ln EV/EBITDA reg. Beta & ln oil price**

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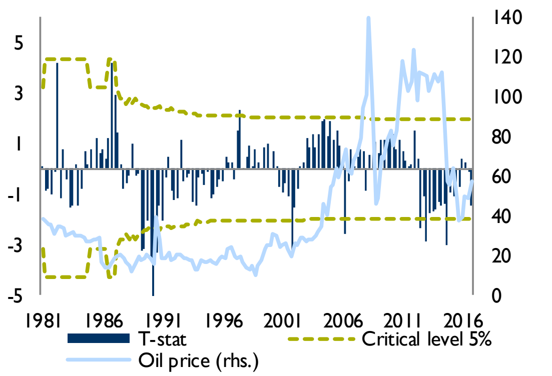
**E&P-Ln EV/EBITDA reg. Beta t-stat & oil price**

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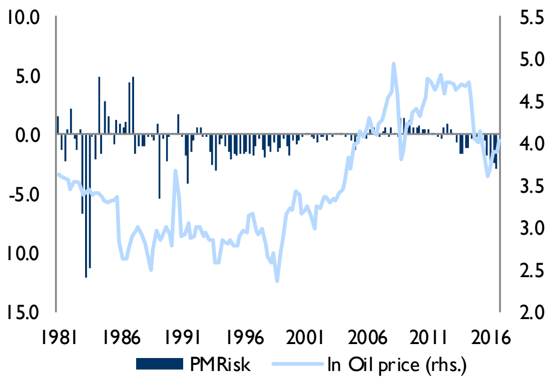
**E&P - Ln EV/EBITDA reg. PMrisk & ln oil price**

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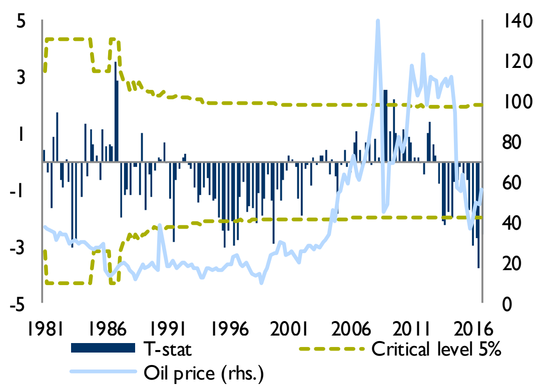
**E&P-Ln EV/EBITDA reg. PMrisk t-stat & oil price**

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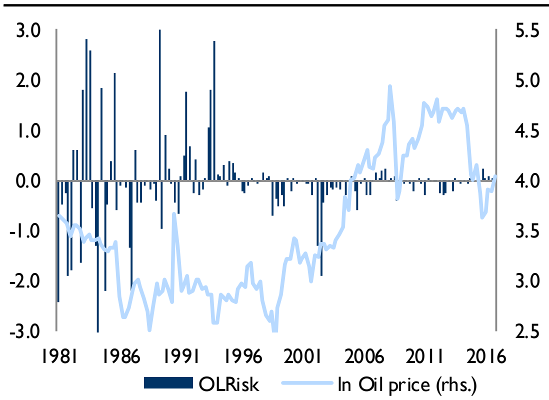
**E&P - Ln EV/EBITDA reg. OLrisk & ln oil price**

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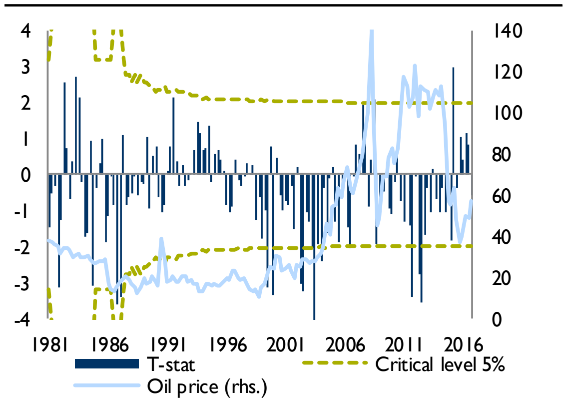
**E&P-Ln EV/EBITDA reg. OLrisk t-stat & oil price**

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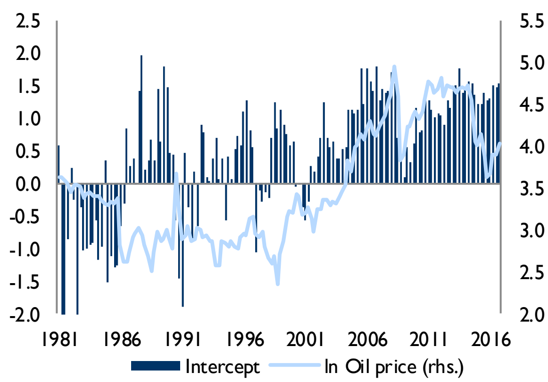
**E&P - Ln EV/Sales reg. Intercept & ln oil price**

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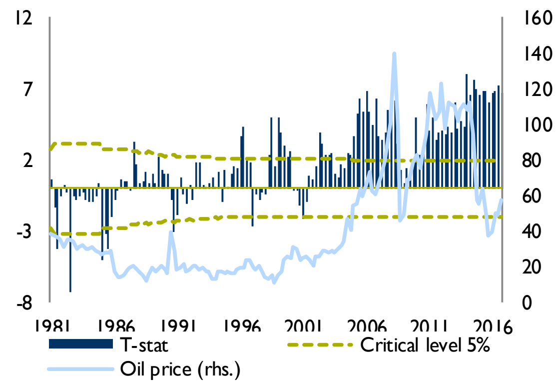
**E&P-Ln EV/Sales reg. Intercept t-stat & oil price**

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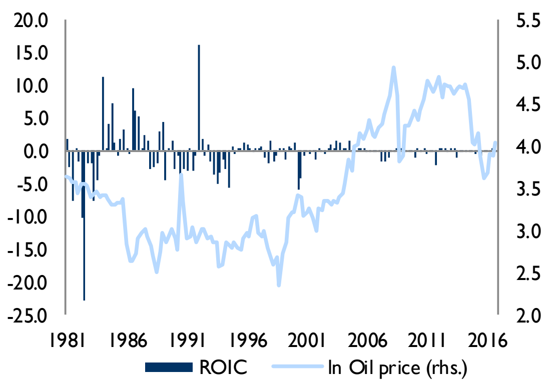
**E&P - Ln EV/Sales reg. ROIC & ln oil price**

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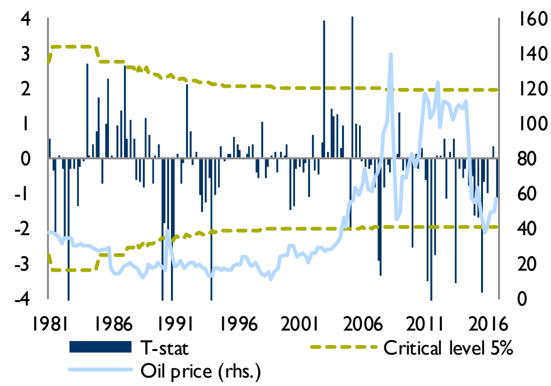
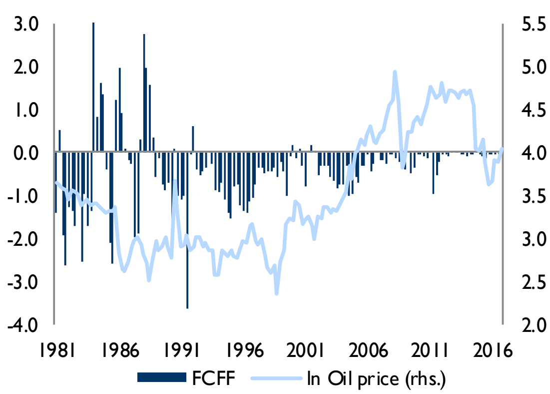
**E&P-Ln EV/Sales reg. ROIC t-stat & oil price**




Source: Own creation

**E&P - Ln EV/Sales reg. FCFF & ln oil price**

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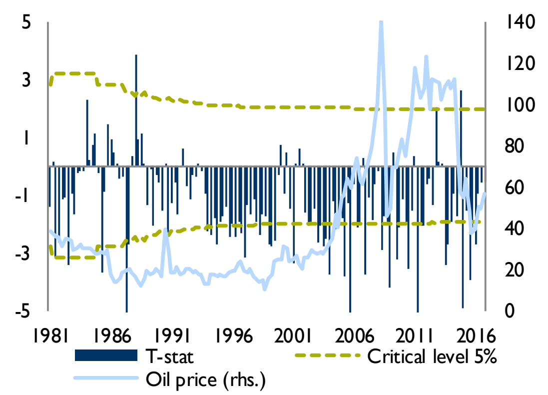
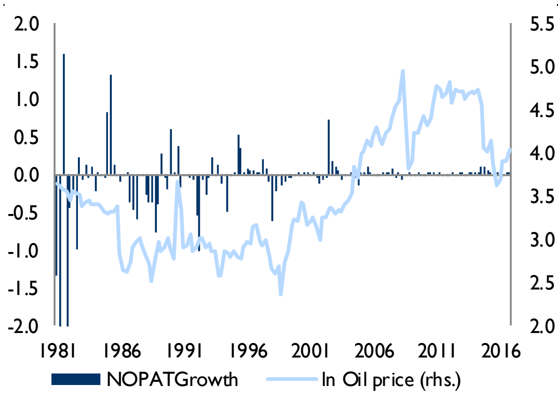



Source: Own creation

**E&P - Ln EV/Sales reg. NOPATg & ln oil price**

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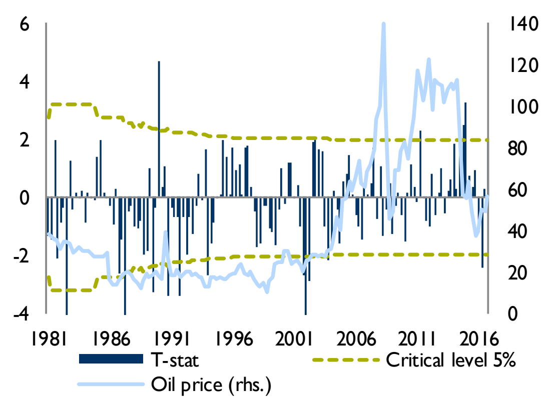
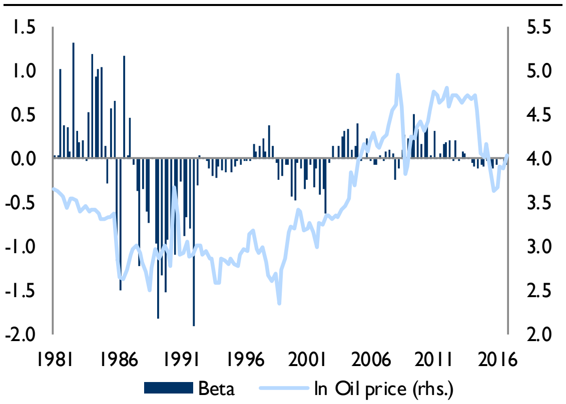
**E&P-Ln EV/Sales reg. NOPATg t-stat & oil price**




Source: Own creation

**E&P - Ln EV/Sales reg. Beta & ln oil price**

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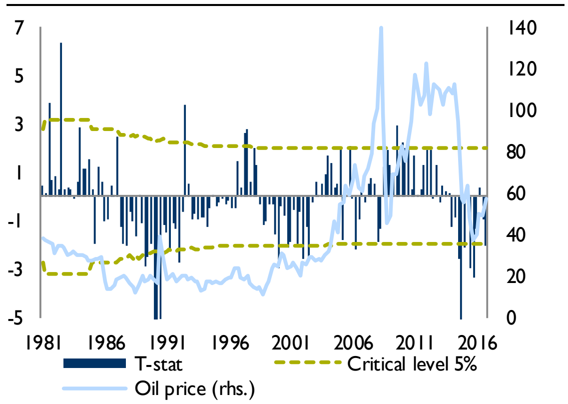
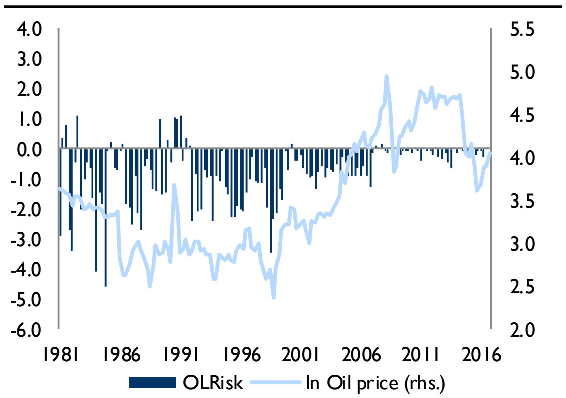
**E&P-Ln EV/Sales reg. Beta t-stat & oil price**




Source: Own creation

**E&P - Ln EV/Sales reg. OLrisk & ln oil price**

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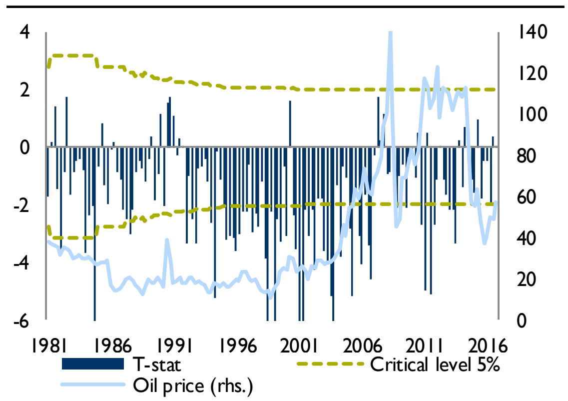
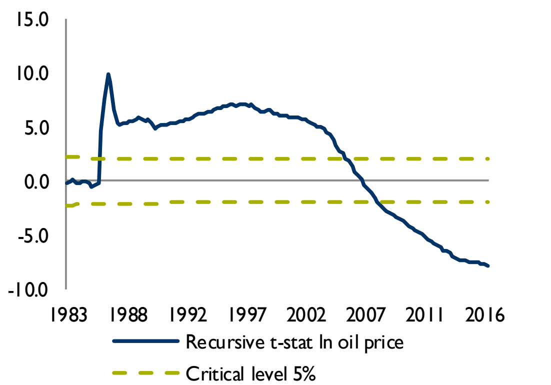
**E&P-Ln EV/Sales reg. OLrisk t-stat & oil price**




Source: Own creation

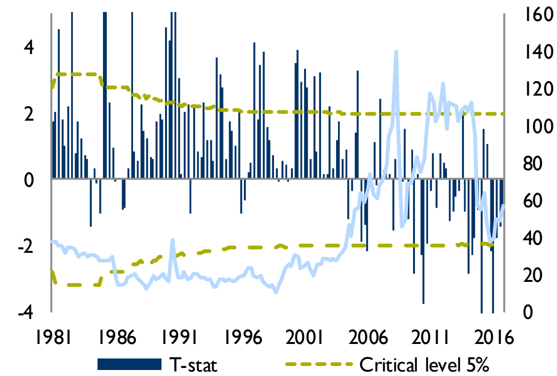
## Appendix 9.2.1

**E&P Ln EV/Sales-Reg. Adj. R-squared on ln oil price**




Source: Own creation

**E&P Ln EV/Sales NOPAT margin t-stat & Oil price**




Source: Own creation

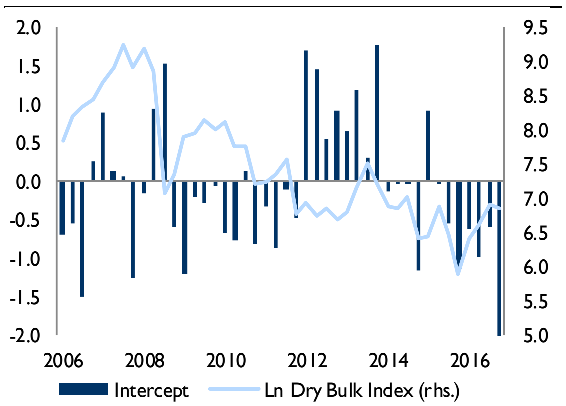
## Appendix 9.2.2

| | Average E&P P/B | Median E&P P/B | Intercept (ln P/B reg.) | Adj. R-squared (rhs.) | Diff (intercept-average) | Adj. R-squared (rhs.) |
|---|---|---|---|---|---|---|
| 1981Q1 | 2.029669726 | 2.093918401 | 4.152370012 | 0.953470099 | 2.122700286 | 0.953470099 |
| 1981Q2 | 1.500580571 | 1.528678452 | 4.533656423 | 0.417772587 | 3.033075852 | 0.417772587 |
| **1981Q3** | **1.277195389** | **1.262709783** | **0.86117029** | **0.766167958** | -0.416025099 | **0.766167958** |
| 1981Q4 | 1.378976575 | 1.725991395 | 1.894465587 | 0.784726621 | 0.515489012 | 0.784726621 |
| 1982Q1 | 1.060909108 | 1.478101556 | 0.168974233 | 0.987460819 | -0.891934875 | 0.987460819 |
| 1982Q2 | 0.958990972 | 1.030620569 | 2.526079273 | 0.911319636 | 1.567088302 | 0.911319636 |
| 2014Q3 | 2.981709418 | 1.767496992 | 4.431223732 | 0.075448593 | 1.449514315 | 0.075448593 |
| 2014Q4 | 2.342355477 | 1.302214546 | 2.871682504 | 0.075852978 | 0.529327027 | 0.075852978 |
| 2015Q1 | 2.257372941 | 1.463544923 | 2.742830031 | 0.048305819 | 0.48545709 | 0.048305819 |
| 2015Q2 | 2.382569426 | 1.486926867 | 2.523650085 | 0.066492521 | 0.141080659 | 0.066492521 |
| 2015Q3 | 1.864415778 | 1.218692928 | 2.498632409 | 0.072095289 | 0.634216631 | 0.072095289 |
| 2015Q4 | 1.895063849 | 1.294574037 | 2.530197058 | 0.106319895 | 0.635133209 | 0.106319895 |
| 2016Q1 | 2.181350252 | 1.503495681 | 2.71189414 | 0.037325786 | 0.530543887 | 0.037325786 |
| 2016Q2 | 2.489748701 | 1.588697135 | 2.833702119 | -0.001391436 | 0.343953418 | -0.001391436 |
| 2016Q3 | 2.541579159 | 1.68625772 | 2.580283575 | 0.044729986 | 0.038704416 | 0.044729986 |
| 2016Q4 | 2.474390646 | 1.861063105 | 2.563345844 | 0.069942626 | 0.088955198 | 0.069942626 |

| | Diff coef. | Intercept |
|---|---|---|
| | 1.128464 | 0.499727 |
| SE | 0.304683 | 0.126345 |
| R squared | 0.088093 | 1.078978 |
| | **13.71763** | **142** |
| | 15.96997 | 165.3155 |
| | #N/A | #N/A |
| T-stat | **3.703732** | |

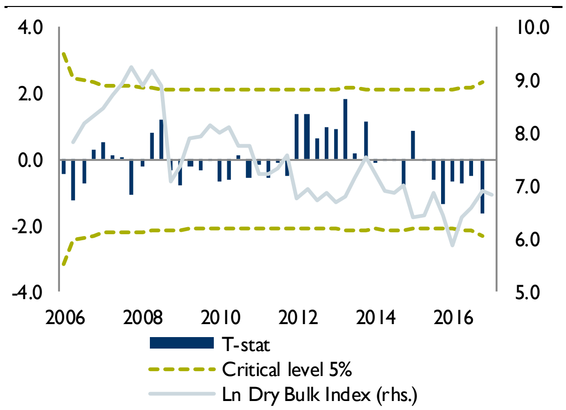
## Appendix 9.2.3

**Dry Bulk - Ln P/B reg. intercept & ln oil price**



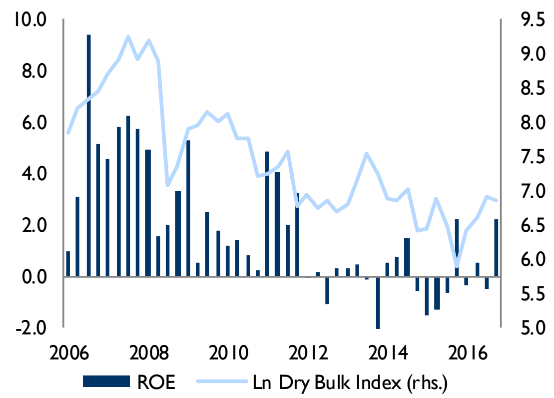

Source: Own creation

**Dry Bulk Ln P/B reg. intercept t-stat & oil price**



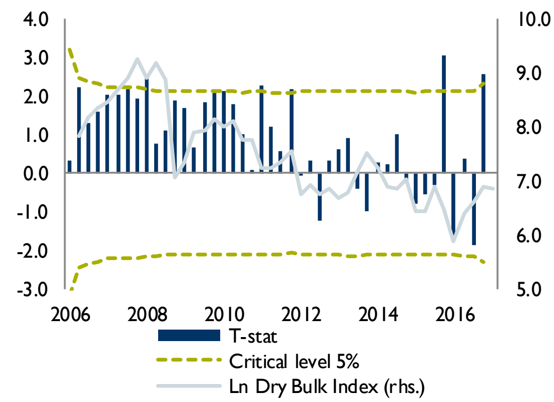

Source: Own creation

**Dry Bulk - Ln P/B reg. ROE & ln oil price**



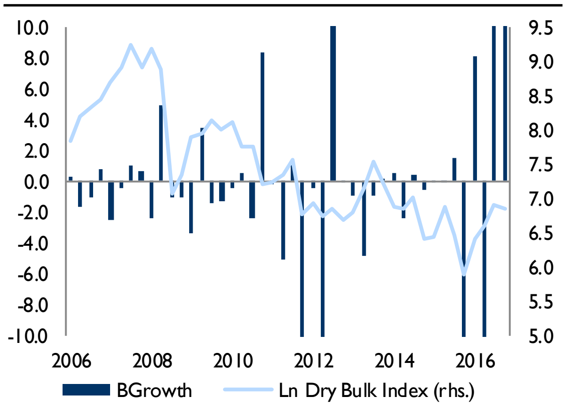

Source: Own creation

**Dry Bulk Ln P/B reg. ROE t-stat & oil price**



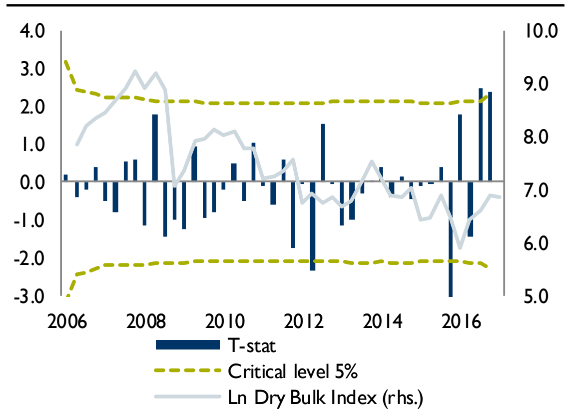

Source: Own creation

**Dry Bulk - Ln P/B reg. Bgrowth & ln oil price**



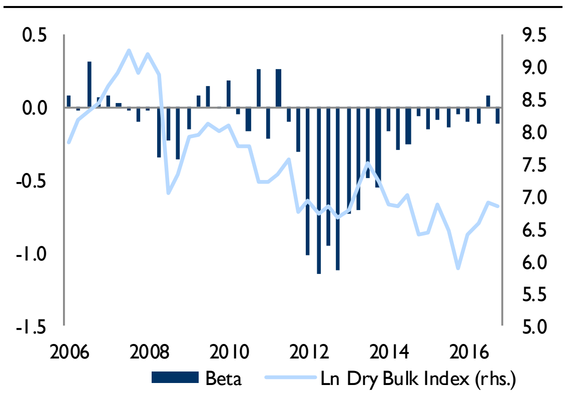

Source: Own creation

**Dry Bulk Ln P/B reg. Bgrowth t-stat & oil price**



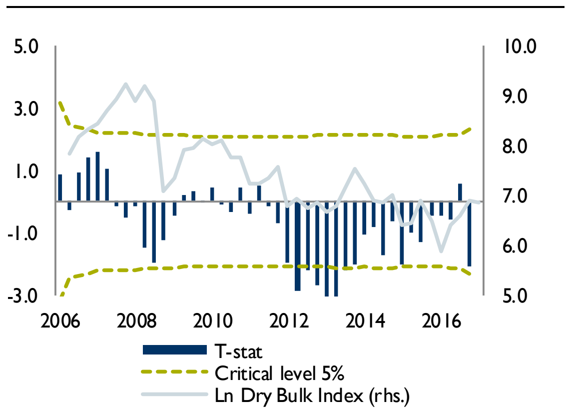

Source: Own creation

**Dry Bulk - Ln P/B reg. Beta & ln oil price**



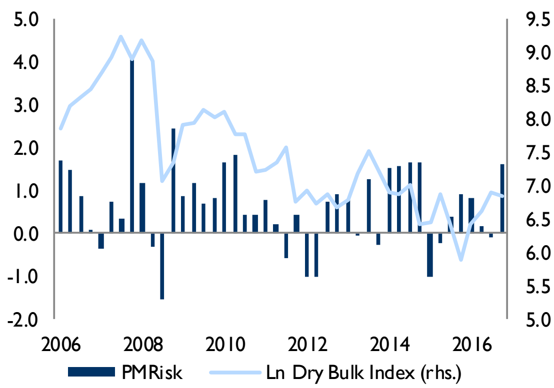

Source: Own creation

**Dry Bulk Ln P/B reg. Beta t-stat & oil price**



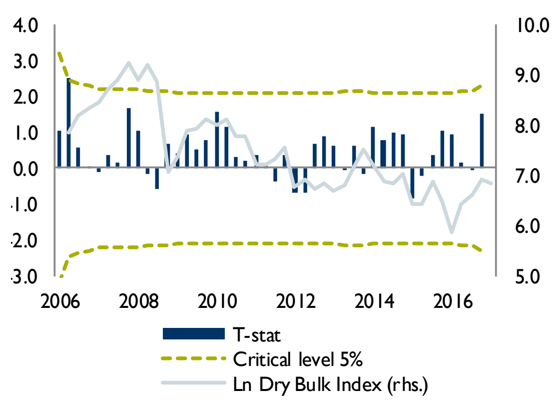

Source: Own creation

**Dry Bulk - Ln P/B reg. PMrisk & ln oil price**



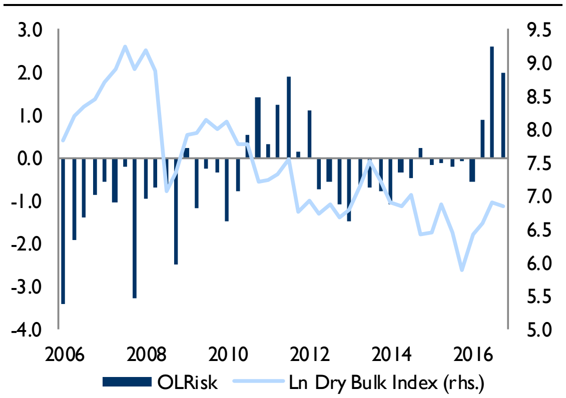

Source: Own creation

**Dry Bulk Ln P/B reg. PMrisk t-stat & oil price**



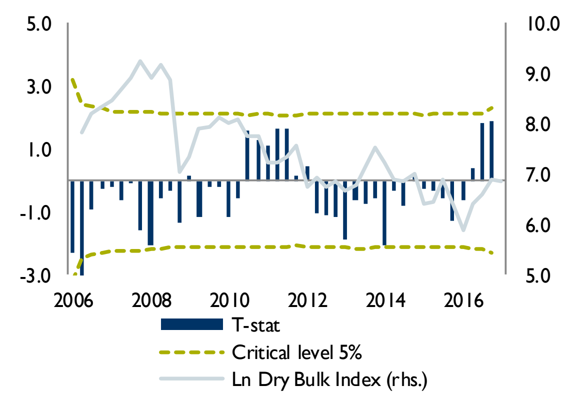

Source: Own creation

**Dry Bulk - Ln P/B reg. OLrisk & ln oil price**



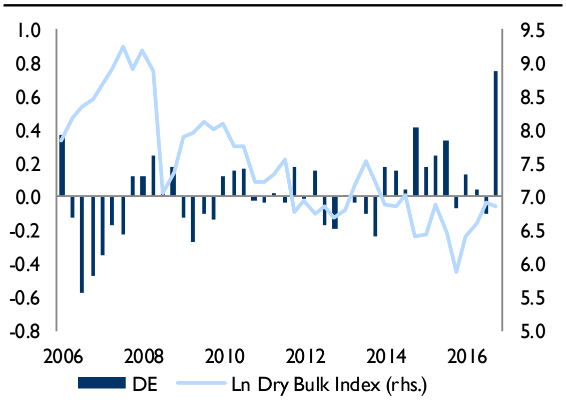

Source: Own creation

**Dry Bulk Ln P/B reg. OLrisk t-stat & oil price**



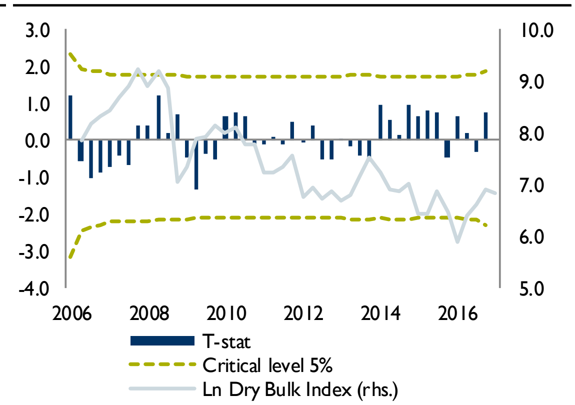

Source: Own creation

**Dry Bulk - Ln P/B reg. Debt/Equity & ln oil price**



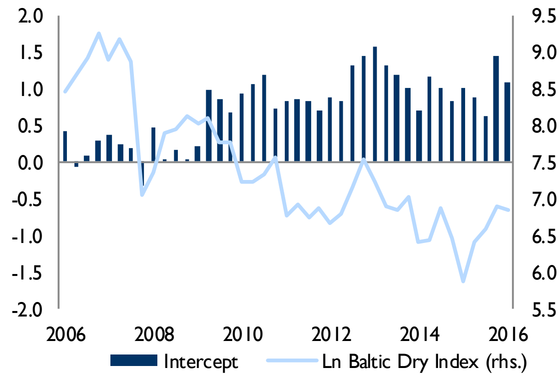

Source: Own creation

**Dry Bulk Ln P/B reg. Debt/Equity t-stat & oil price**



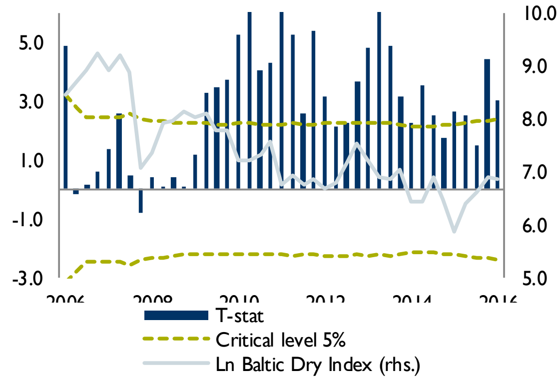

Source: Own creation

**Dry Bulk - Ln EV/Sales reg. intercept & ln oil price**



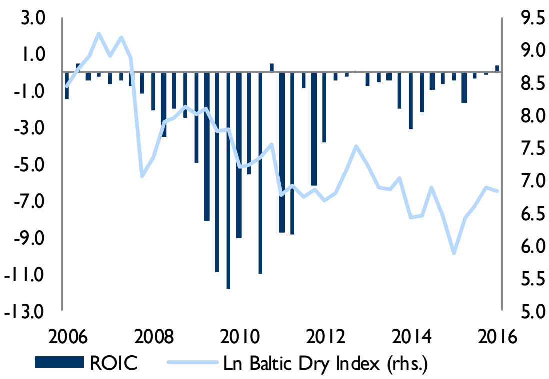

Source: Own creation

**Dry Bulk Ln EV/Sales reg. intercept t-stat & oil price**



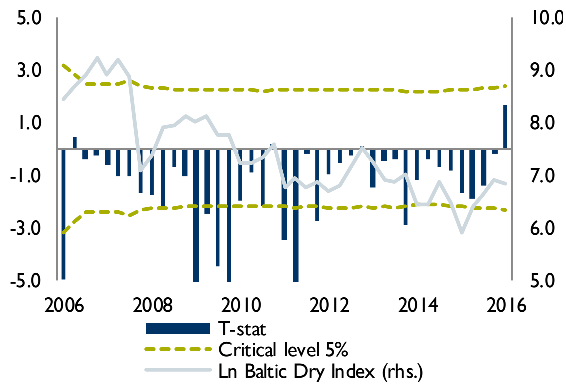

Source: Own creation

**Dry Bulk - Ln EV/Sales reg. ROIC & ln oil price**



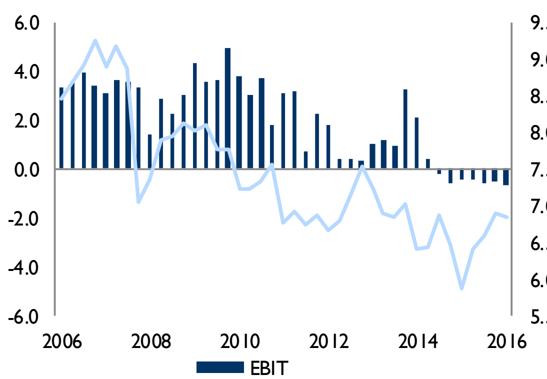

Source: Own creation

**Dry Bulk Ln EV/Sales reg. ROIC t-stat & oil price**



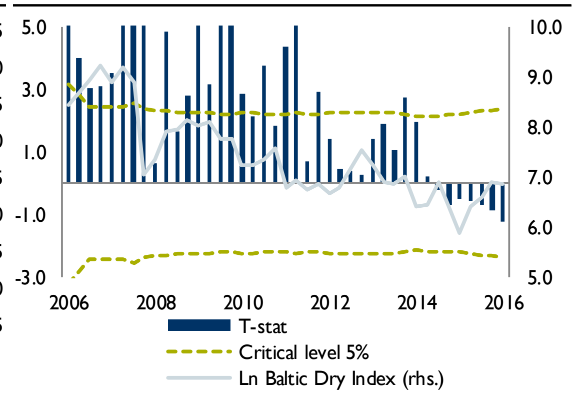

Source: Own creation

**Dry Bulk - Ln EV/Sales reg. EBIT & ln oil price**



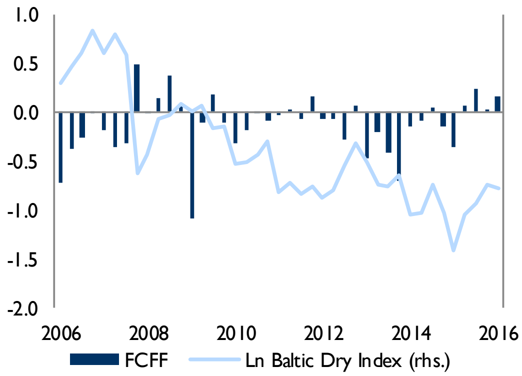

Source: Own creation

**Dry Bulk Ln EV/Sales reg. EBIT t-stat & oil price**



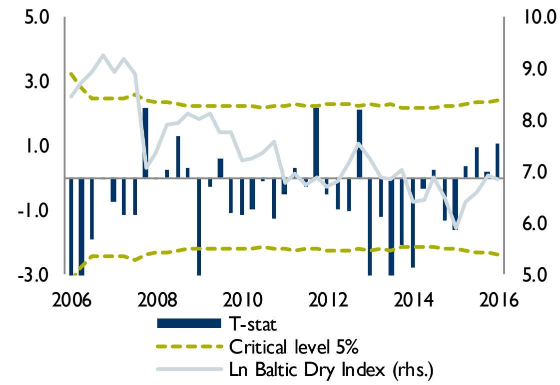

Source: Own creation

**Dry Bulk - Ln EV/Sales reg. FCFF & ln oil price**



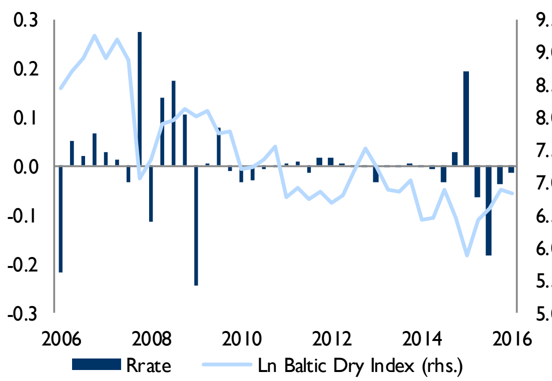

Source: Own creation

**Dry Bulk Ln EV/Sales reg. FCFF t-stat & oil price**



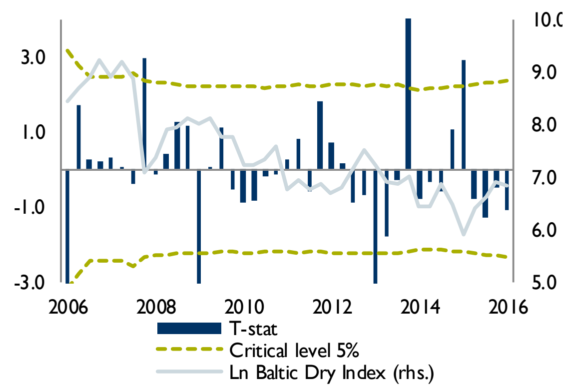

Source: Own creation

**Dry Bulk - Ln EV/Sales reg. Rrate & ln oil price**



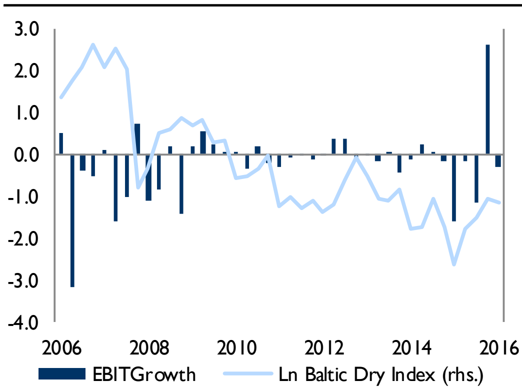

Source: Own creation

**Dry Bulk Ln EV/Sales reg. Rrate t-stat & oil price**



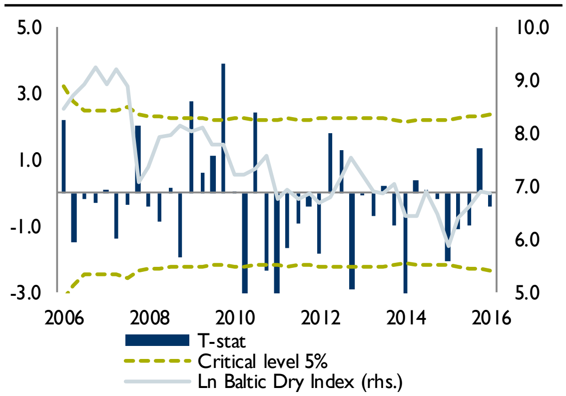

Source: Own creation

**Dry Bulk - Ln EV/Sales reg. EBITg & ln oil price**



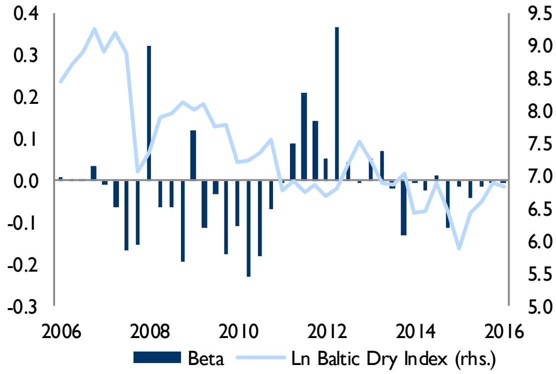

Source: Own creation

**Dry Bulk Ln EV/Sales reg. EBITg t-stat & oil price**



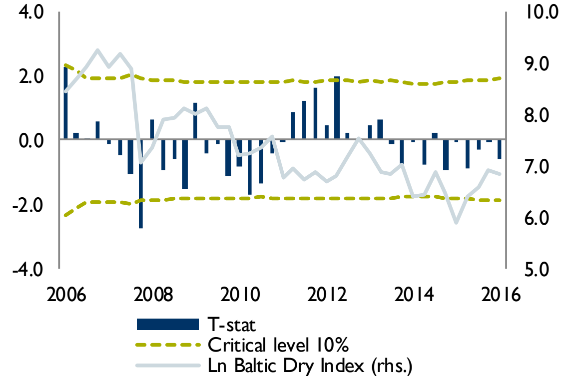

Source: Own creation

**Dry Bulk - Ln EV/Sales reg. Beta & ln oil price**



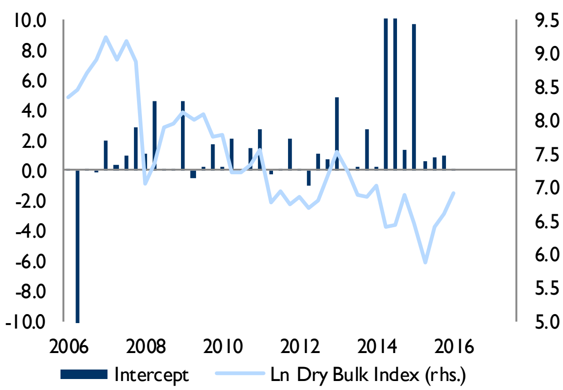

Source: Own creation

**Dry Bulk Ln EV/Sales reg. Beta t-stat & oil price**



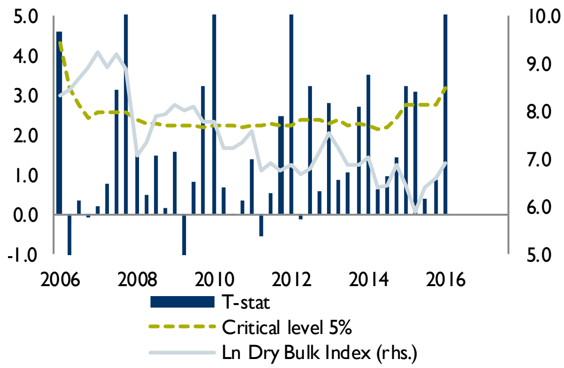

Source: Own creation

**Dry Bulk-Ln EV/EBITDa reg. Intercept & ln oil price**



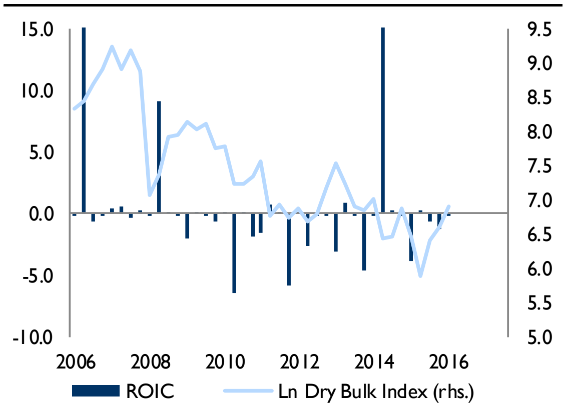

Source: Own creation

**Dry BulkLnEV/EBITDA. Intercept t-stat & oil price**



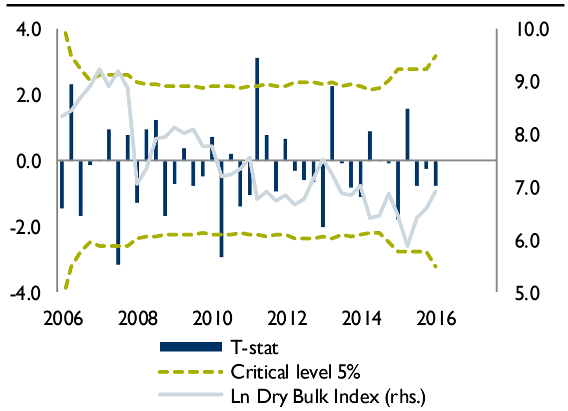

Source: Own creation

**Dry Bulk-Ln EV/EBITDa reg. ROIC & ln oil price**



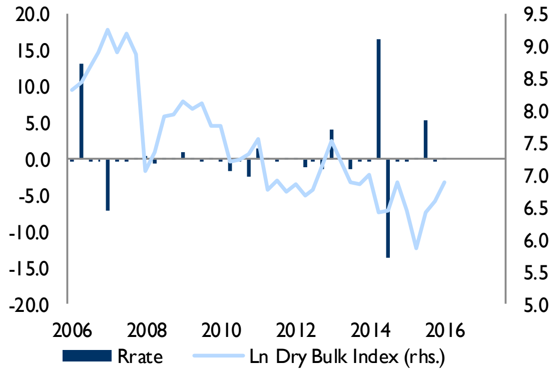

Source: Own creation

**Dry BulkLnEV/EBITDA. ROIC t-stat & oil price**



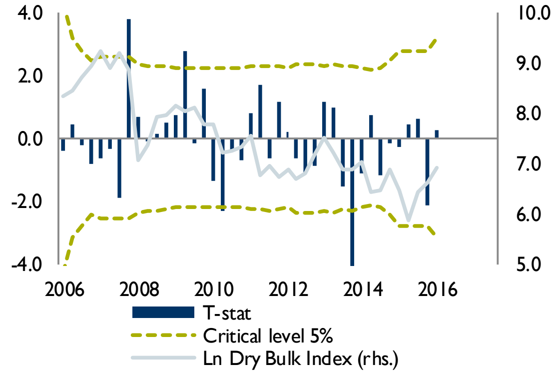

Source: Own creation

**Dry Bulk-Ln EV/EBITDa reg. Rrate & ln oil price**



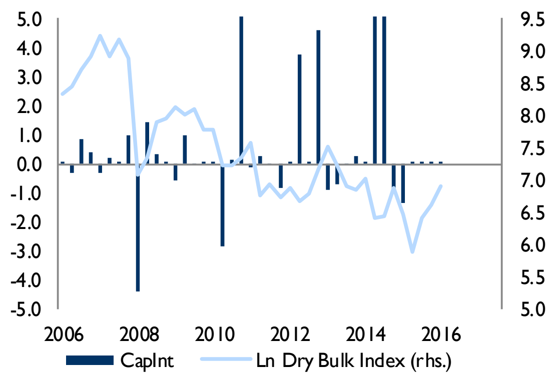

Source: Own creation

**Dry BulkLnEV/EBITDA. Rrate t-stat & oil price**



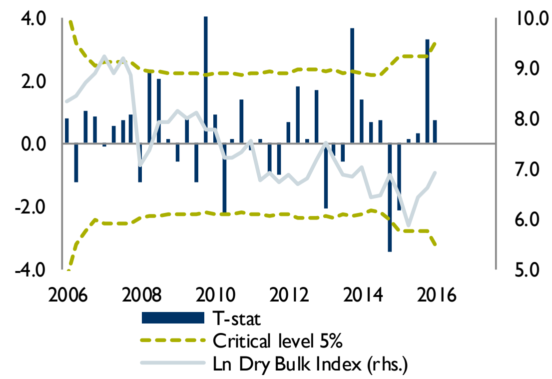

Source: Own creation

**Dry Bulk-Ln EV/EBITDa reg. CapInt & ln oil price**



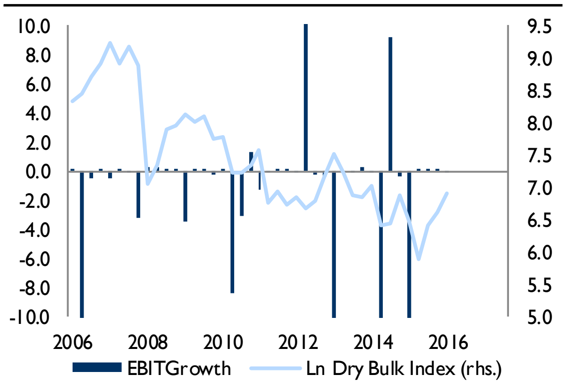

Source: Own creation

**Dry BulkLnEV/EBITDA. CapInt t-stat & oil price**



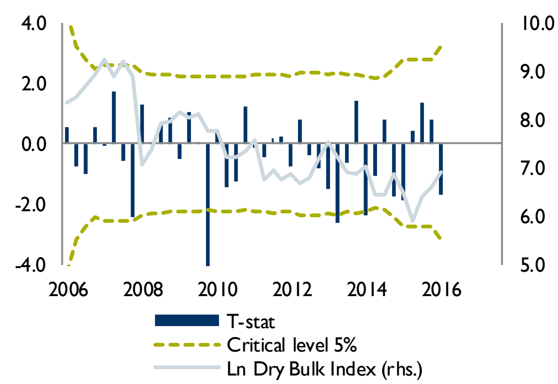

Source: Own creation

**Dry Bulk-Ln EV/EBITDa reg. EBITg & ln oil price**



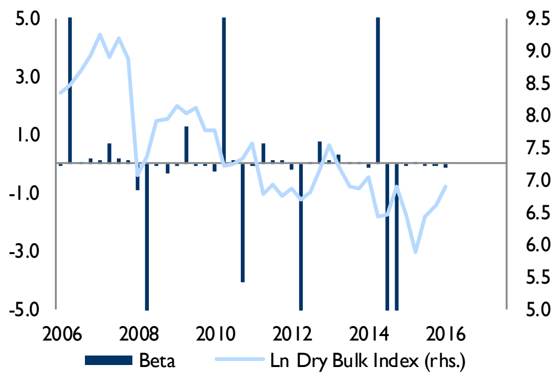

Source: Own creation

**Dry BulkLnEV/EBITDA. EBITg t-stat & oil price**



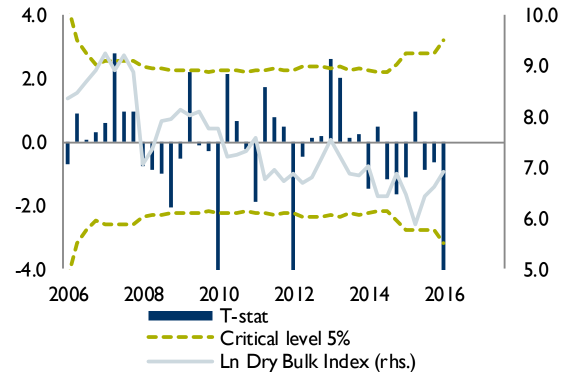

Source: Own creation

**Dry Bulk-Ln EV/EBITDa reg. Beta & ln oil price**



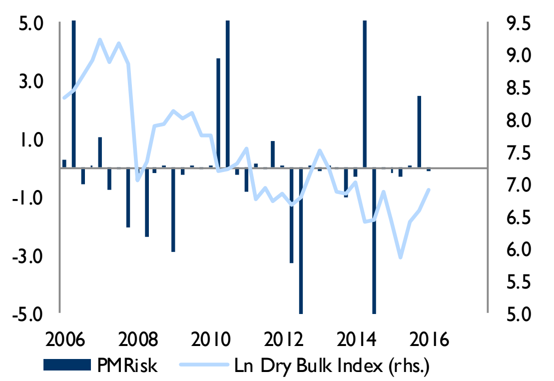

Source: Own creation

**Dry BulkLnEV/EBITDA. Beta t-stat & oil price**



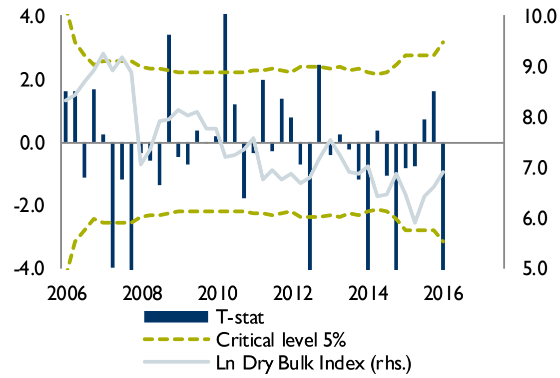

Source: Own creation

**Dry Bulk-Ln EV/EBITDa reg. PMrisk & ln oil price**




Source: Own creation

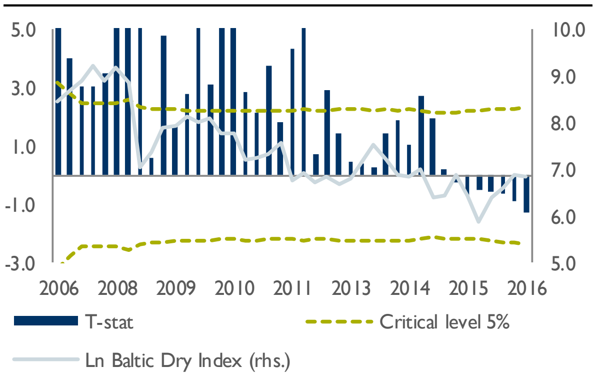
**Dry BulkLnEV/EBITDA. PMrisk t-stat & oil price**




Source: Own creation

*Appendix 9.2.3.1*

**Dry Bulk Ln EV/Sales T-test EBIT & Baltic Dry Index**




Source: Own creation

## APPENDIX 9.4 FINAL REGRESSIONS RESULTS

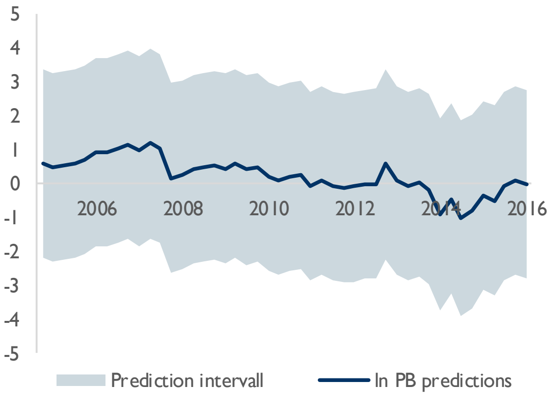
### Appendix 9.4.1 Dry bulk results

| ln P/B | 2016Q4 - 2005Q3 |
|---|---|
| R-squared | 0.09 |
| Adj. R-squared | 0.08 |
| F-stat | 26.49 |
| P-value F-stat | 0.00 |
| Std. of estimate | 1.41 |
| CI | 277.48 |
| k | 5 |
| n | 1,143 |
| Intercept | |
| Alpha | -3.13 |
| Std | 0.39 |
| T-stat | -7.94 |
| P-value | 0.00 |
| Beta | |
| Beta | -0.06 |
| Std | 0.02 |
| T-stat | -3.63 |
| P-value | 0.00 |
| VIF | 1.02 |
| SGrowth | |
| Beta | 0.53 |
| Std | 0.26 |
| T-stat | 2.00 |
| P-value | 0.05 |
| VIF | 1.16 |
| FCFF | |
| Beta | 0.04 |
| Std | 0.02 |
| T-stat | 2.68 |
| P-value | 0.01 |
| VIF | 1.13 |
| LN_BDI | |
| Beta | 0.46 |
| Std | 0.05 |
| T-stat | 8.84 |
| P-value | 0.00 |
| VIF | 1.05 |

| ln EV/Sales | 2016Q4 - 2007Q3 |
|---|---|
| R-squared | 0.20 |
| Adj. R-squared | 0.19 |
| F-stat | 26.74 |
| P-value F-stat | 0.00 |
| Std. of estimate | 0.89 |
| CI | 9.35 |
| k | 7 |
| n | 659 |
| Intercept | |
| Alpha | 0.86 |
| Std | 0.10 |
| T-stat | 8.25 |
| P-value | 0.00 |
| ROE | |
| Beta | 0.01 |
| Std | 0.00 |
| T-stat | 4.05 |
| P-value | 0.00 |
| VIF | 1.35 |
| EBITDA | |
| Beta | 0.59 |
| Std | 0.21 |
| T-stat | 2.86 |
| P-value | 0.00 |
| VIF | 1.03 |
| Beta | |
| Beta | -0.03 |
| Std | 0.02 |
| T-stat | -1.54 |
| P-value | 0.12 |
| VIF | 1.03 |
| EBITGrowth3 | |
| Beta | 0.01 |
| Std | 0.00 |
| T-stat | 4.63 |
| P-value | 0.00 |
| VIF | 1.02 |
| FCFF | |
| Beta | -0.08 |
| Std | 0.03 |
| T-stat | -3.13 |
| P-value | 0.00 |
| VIF | 1.36 |
| BDIGrowth1 | |
| Beta | 0.90 |
| Std | 0.25 |
| T-stat | 3.68 |
| P-value | 0.00 |
| VIF | 1.04 |

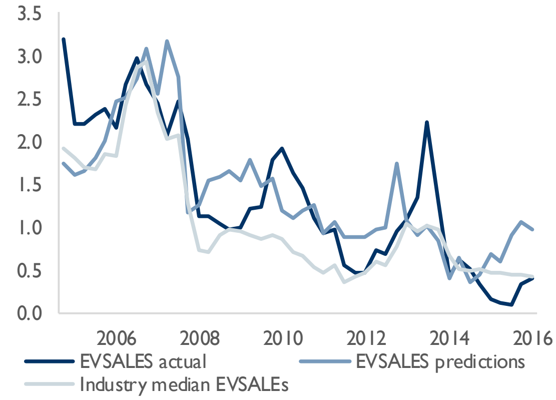
| ln EV/EBITDA | 2016Q4 - 2008Q3 |
|---|---|
| R-squared | 0.42 |
| Adj. R-squared | 0.41 |
| F-stat | 69.60 |
| P-value F-stat | 0.00 |
| Std. of estimate | 0.82 |
| CI | 5.63 |
| k | 7 |
| n | 593 |
| Intercept | |
| Alpha | 2.80 |
| Std | 0.11 |
| T-stat | 26.65 |
| P-value | 0.00 |
| CapInt | |
| Beta | 0.03 |
| Std | 0.01 |
| T-stat | 2.39 |
| P-value | 0.02 |
| VIF | 1.08 |
| EBITGrowth3 | |
| Beta | 0.01 |
| Std | 0.00 |
| T-stat | 3.02 |
| P-value | 0.00 |
| VIF | 1.01 |
| Beta | |
| Beta | -0.07 |
| Std | 0.03 |
| T-stat | -2.41 |
| P-value | 0.02 |
| VIF | 1.07 |
| EBITDA | |
| Beta | -1.36 |
| Std | 0.17 |
| T-stat | -8.03 |
| P-value | 0.00 |
| VIF | 1.04 |
| FCFF | |
| Beta | -0.14 |
| Std | 0.04 |
| T-stat | -3.34 |
| P-value | 0.00 |
| VIF | 1.02 |
| BDIGrowth1 | |
| Beta | 0.63 |
| Std | 0.24 |
| T-stat | 2.57 |
| P-value | 0.01 |
| VIF | 1.05 |

**GOGL prediction interval**




Source: Own creation

**GOGL P/B predictions**



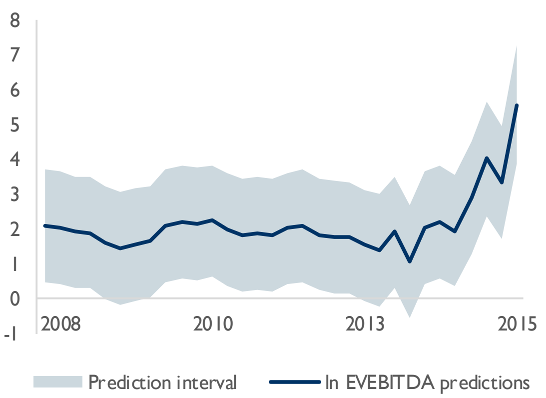

Source: Own creation

**GOGL in ln P/B Dry Bulk regression variables percentile distribution (2016Q4)**

| Percentile | ln PB | Beta | Sales growth | FCFF-margin |
|---|---|---|---|---|
| 10% | -2.84 | 3.22 | -0.21 | **-0.40** |
| 20% | -1.76 | **0.52** | -0.12 | -0.25 |
| 30% | -1.59 | 0.48 | -0.09 | 0.20 |
| 40% | -1.32 | -0.19 | -0.06 | 0.56 |
| 50% | **-0.97** | -0.34 | -0.04 | 0.60 |
| 60% | **-0.65** | -0.42 | -0.03 | 1.14 |
| 70% | 0.20 | -0.77 | 0.00 | 1.68 |
| 80% | 0.72 | -1.29 | **0.02** | 3.84 |
| 90% | 1.23 | -1.75 | 0.14 | 6.26 |

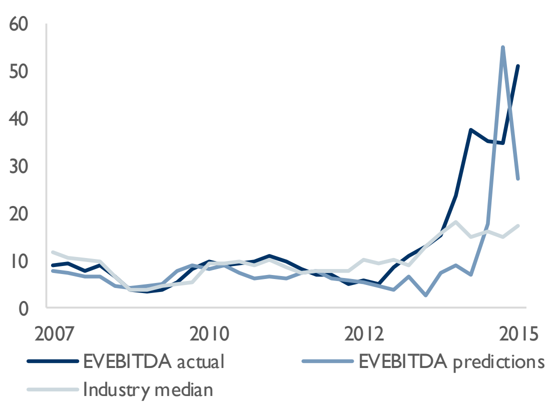
Source: Own creation

**GOGL prediction interval**




Source: Own creation

**GOGL EV/EBITDA predictions**




Source: Own creation

**GOGL in ln EV/EBITDA Dry Bulk regression variables percentile distribution (2015Q2)**

| Percentile | ln EVEBITDA | Capital intensity | EBIT growth 3yr | Beta | EBITDA-margin | FCFF-margin |
|---|---|---|---|---|---|---|
| **10%** | 0.57 | 4.34 | -1.12 | 6.13 | 0.05 | **-2.90** |
| **20%** | 1.46 | **3.01** | **-1.08** | 5.65 | **0.11** | -0.85 |
| **30%** | 1.79 | 1.46 | -0.81 | 5.04 | 0.20 | -0.42 |
| **40%** | 2.10 | 1.33 | -0.61 | **3.25** | 0.20 | -0.32 |
| **50%** | 2.47 | 0.71 | -0.20 | 2.46 | 0.22 | 0.05 |
| **60%** | 2.57 | 0.61 | -0.19 | 1.53 | 0.28 | 0.08 |
| **70%** | 2.87 | 0.49 | 0.02 | 1.36 | 0.37 | 0.27 |
| **80%** | 3.10 | 0.46 | 0.03 | 0.89 | 0.48 | 0.33 |
| **90%** | **5.10** | 0.43 | 0.17 | 0.16 | 0.63 | 0.55 |

Source: Own creation

## Appendix 9.4.2 E&P results

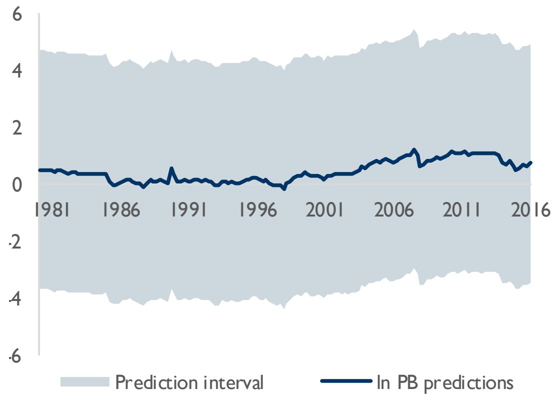
| ln P/B | 2016Q4 - 1981Q1 |
|---|---|
| **R-squared** | 0.03 |
| **Adj. R-squared** | 0.03 |
| **F-stat** | 75.22 |
| **P-value F-stat** | 0.00 |
| **Std. of estimate** | 2.13 |
| **CI** | 259.98 |
| **k** | 5 |
| **n** | 9,700 |
| **Intercept** | |
| **Alpha** | -1.49 |
| **Std** | 0.12 |
| **T-stat** | -12.52 |
| **P-value** | 0.00 |
| **EBITDA** | |
| **Beta** | 0.00 |
| **Std** | 0.00 |
| **T-stat** | 2.52 |
| **P-value** | 0.01 |
| **VIF** | 1.06 |
| **FCFF** | |
| **Beta** | 0.00 |
| **Std** | 0.00 |
| **T-stat** | 2.97 |
| **P-value** | 0.00 |
| **VIF** | 1.11 |
| **BGrowth5** | |
| **Beta** | 0.03 |
| **Std** | 0.01 |
| **T-stat** | 2.28 |
| **P-value** | 0.02 |
| **VIF** | 1.05 |
| **LN_Oil** | |
| **Beta** | 0.55 |
| **Std** | 0.03 |
| **T-stat** | 18.20 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |

| ln P/E | 2016Q4 - 1981Q1 |
|---|---|
| **R-squared** | 0.02 |
| **Adj. R-squared** | 0.02 |
| **F-stat** | 23.04 |
| **P-value F-stat** | 0.00 |
| **Std. of estimate** | 2.03 |
| **CI** | 739.67 |
| **k** | 7 |
| **n** | 5,618 |
| **Intercept** | |
| **Alpha** | 1.24 |
| **Std** | 0.14 |
| **T-stat** | 8.60 |
| **P-value** | 0.00 |
| **Beta** | |
| **Beta** | -0.00 |
| **Std** | 0.00 |
| **T-stat** | -1.50 |
| **P-value** | 0.13 |
| **VIF** | 1.00 |
| **SGrowth5** | |
| **Beta** | 0.00 |
| **Std** | 0.00 |
| **T-stat** | 2.54 |
| **P-value** | 0.01 |
| **VIF** | 1.00 |
| **ROIC** | |
| **Beta** | 0.01 |
| **Std** | 0.00 |
| **T-stat** | 2.06 |
| **P-value** | 0.04 |
| **VIF** | 1.00 |
| **EBITDA** | |
| **Beta** | 0.30 |
| **Std** | 0.11 |
| **T-stat** | 2.80 |
| **P-value** | 0.01 |
| **VIF** | 1.01 |
| **FCFF** | |
| **Beta** | 0.00 |
| **Std** | 0.00 |
| **T-stat** | 1.72 |
| **P-value** | 0.08 |
| **VIF** | 1.00 |
| **LN_Oil** | |
| **Beta** | 0.32 |
| **Std** | 0.04 |
| **T-stat** | 8.37 |
| **P-value** | 0.00 |
| **VIF** | 1.01 |

| ln EV/Sales | 2016Q4 - 1985Q1 |
|---|---|
| **R-squared** | 0.05 |
| **Adj. R-squared** | 0.05 |
| **F-stat** | 48.95 |
| **P-value F-stat** | 0.00 |
| **Std. of estimate** | 1.64 |
| **CI** | 28.93 |
| **k** | 6 |
| **n** | 4,251 |
| **Intercept** | |
| **Alpha** | -1.62 |
| **Std** | 0.14 |
| **T-stat** | -11.84 |
| **P-value** | 0.00 |
| **ROIC** | |
| **Beta** | -0.05 |
| **Std** | 0.01 |
| **T-stat** | -4.04 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |
| **EBITDA** | |
| **Beta** | -0.02 |
| **Std** | 0.00 |
| **T-stat** | -9.30 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |
| **Rrate** | |
| **Beta** | 0.00 |
| **Std** | 0.00 |
| **T-stat** | 3.59 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |
| **NOPATGrowth5** | |
| **Beta** | 0.00 |
| **Std** | 0.00 |
| **T-stat** | 7.54 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |
| **LN_Oil** | |
| **Beta** | 0.55 |
| **Std** | 0.03 |
| **T-stat** | 15.84 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |

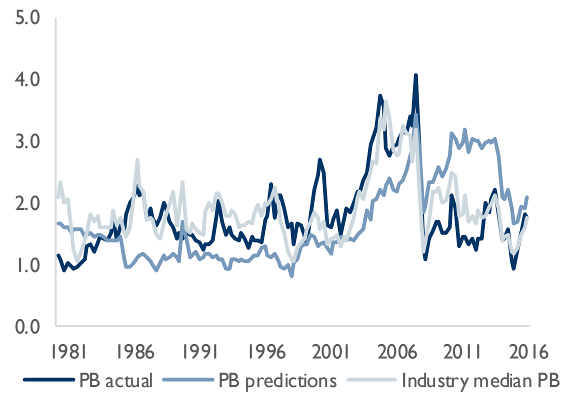
| ln EV/EBITDA | 2016Q4 - 1987Q1 |
|---|---|
| **R-squared** | 0.05 |
| **Adj. R-squared** | 0.05 |
| **F-stat** | 81.35 |
| **P-value F-stat** | 0.00 |
| **Std. of estimate** | 1.49 |
| **CI** | 85.64 |
| **k** | 5 |
| **n** | 6,727 |
| **Intercept** | |
| **Alpha** | 0.57 |
| **Std** | 0.09 |
| **T-stat** | 6.48 |
| **P-value** | 0.00 |
| **ROIC** | |
| **Beta** | -0.01 |
| **Std** | 0.00 |
| **T-stat** | -1.65 |
| **P-value** | 0.10 |
| **VIF** | 1.00 |
| **CapInt** | |
| **Beta** | 0.05 |
| **Std** | 0.01 |
| **T-stat** | 3.55 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |
| **SGrowth5** | |
| **Beta** | -0.00 |
| **Std** | 0.00 |
| **T-stat** | -3.26 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |
| **LN_Oil** | |
| **Beta** | 0.36 |
| **Std** | 0.02 |
| **T-stat** | 15.70 |
| **P-value** | 0.00 |
| **VIF** | 1.00 |

**EGN prediction interval**




Source: Own creation

**EGN P/B predictions**



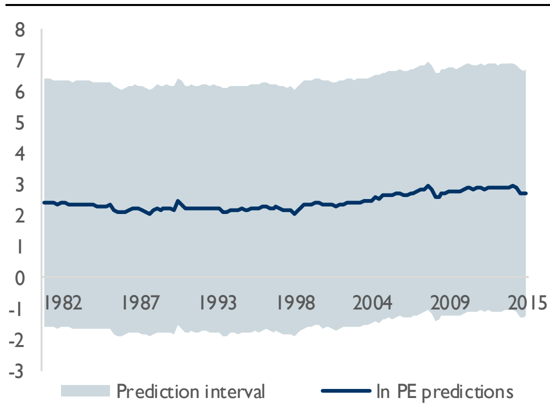

Source: Own creation

**EGN in ln P/B E&P regression variables percentile distribution (2016Q4)**

| Percentile | LN_PB | EBITDA | FCFF | BGrowth5 |
|---|---|---|---|---|
| 1% | -6.28 | -2.41 | -13.47 | -0.20 |
| 5% | -2.45 | -1.67 | -2.67 | -0.14 |
| 10% | -0.97 | -0.85 | -1.14 | -0.07 |
| 15% | -0.62 | -0.46 | -0.28 | -0.03 |
| 20% | -0.30 | -0.24 | -0.14 | 0.00 |
| 25% | -0.30 | -0.24 | -0.14 | 0.00 |
| 30% | 0.18 | 0.02 | -0.01 | 0.04 |
| 35% | 0.28 | 0.03 | 0.01 | 0.05 |
| 40% | 0.38 | 0.05 | 0.02 | 0.06 |
| 45% | 0.43 | 0.07 | 0.03 | **0.08** |
| 50% | 0.62 | 0.10 | 0.05 | **0.09** |
| 55% | **0.69** | 0.10 | 0.07 | 0.10 |
| 60% | **0.78** | 0.14 | 0.10 | 0.12 |
| 65% | 0.90 | 0.17 | 0.16 | 0.15 |
| 70% | 1.13 | 0.22 | 0.25 | 0.18 |
| 75% | 1.41 | 0.29 | 0.35 | 0.21 |
| 80% | 1.71 | **0.37** | 0.38 | 0.22 |
| 85% | 2.94 | **0.44** | 0.56 | 0.29 |
| 90% | 5.02 | 0.52 | **0.66** | 0.53 |
| 95% | 6.88 | 0.71 | **1.13** | 2.08 |
| 99% | 8.76 | 0.88 | 3.17 | 10.27 |

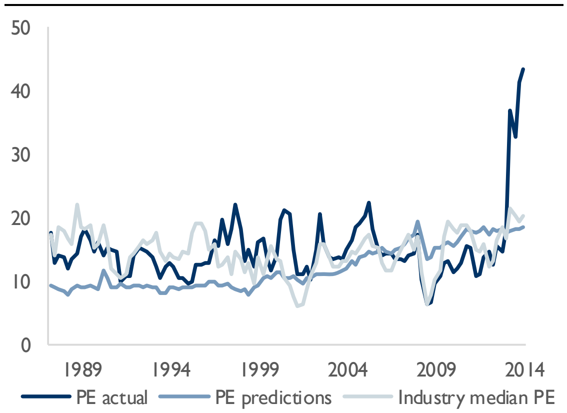
Source: Own creation

**EGN prediction interval**




Source: Own creation

**EGN P/E predictions**



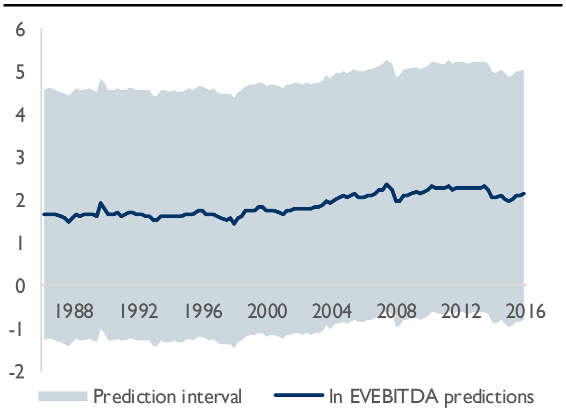

Source: Own creation

**EGN in ln P/E E&P regression variables percentile distribution (2015Q2)**

| Percentile | ln PE | Beta | Sales growth 5yr | ROIC | EBITDA-margin | FCFF-margin |
|---|---|---|---|---|---|---|
| 1% | -4.31 | 4.62 | -0.21 | -0.89 | -0.01 | -2.63 |
| 5% | -2.13 | 4.07 | -0.11 | -0.05 | 0.01 | -1.24 |
| 10% | 0.99 | 3.06 | -0.02 | 0.00 | 0.02 | -0.91 |
| 15% | 1.42 | 2.55 | 0.03 | 0.01 | 0.05 | -0.76 |
| 20% | 1.81 | 2.32 | 0.06 | 0.02 | 0.07 | -0.62 |
| 25% | 1.97 | 1.79 | 0.09 | 0.02 | 0.08 | -0.44 |
| 30% | 2.11 | 1.63 | 0.11 | 0.04 | 0.13 | -0.26 |
| 35% | 2.38 | 1.48 | 0.12 | 0.05 | 0.18 | -0.21 |
| 40% | 2.48 | 1.34 | 0.13 | 0.06 | 0.28 | -0.14 |
| 45% | 2.57 | 1.21 | 0.15 | 0.07 | 0.35 | -0.06 |
| 50% | 2.76 | 1.14 | 0.16 | 0.07 | 0.40 | -0.02 |
| 55% | 2.94 | 1.01 | 0.18 | 0.08 | 0.45 | 0.00 |
| 60% | 3.10 | 0.91 | 0.20 | 0.09 | 0.48 | 0.02 |
| 65% | 3.28 | 0.83 | 0.23 | 0.11 | 0.54 | 0.03 |
| 70% | 3.52 | 0.67 | 0.25 | 0.12 | 0.57 | 0.07 |
| 75% | 4.02 | 0.56 | 0.29 | 0.13 | 0.60 | 0.09 |
| 80% | 4.20 | 0.46 | 0.35 | 0.17 | 0.63 | 0.15 |
| 85% | 5.29 | 0.19 | 0.39 | 0.19 | 0.65 | 0.28 |
| 90% | 6.29 | 0.03 | 0.73 | 0.29 | 0.69 | 0.73 |
| 95% | 8.65 | -0.42 | 1.20 | 0.41 | 0.73 | 1.12 |
| 99% | 14.26 | -1.24 | 6.00 | 0.77 | 0.85 | 5.29 |

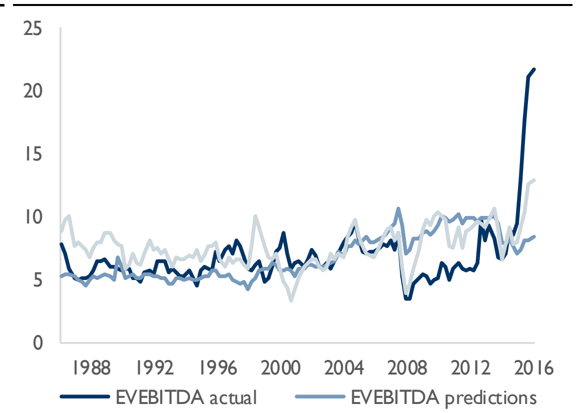
Source: Own creation

**EGN prediction interval**




Source: Own creation

**EGN EV/EBITDA predictions**




Source: Own creation

**EGN in ln EV/EBITDA E&P regression variables percentile distribution (2016Q4)**

| Percentile | LN_EVEBITDA | ROIC | CapInt | SGrowth5 |
|---|---|---|---|---|
| **1%** | 0.98 | -0.34 | 5.92 | -0.24 |
| **5%** | 1.00 | -0.29 | 4.20 | -0.22 |
| **10%** | 1.16 | -0.12 | 4.09 | **-0.13** |
| **15%** | 1.45 | -0.09 | 3.32 | -0.06 |
| **20%** | 1.74 | -0.07 | 2.21 | -0.04 |
| **25%** | 1.86 | -0.06 | 1.99 | -0.02 |
| **30%** | 1.98 | **-0.05** | 1.88 | -0.01 |
| **35%** | **2.12** | -0.03 | 1.73 | 0.01 |
| **40%** | **2.32** | -0.02 | 1.19 | 0.01 |
| **45%** | 2.55 | 0.00 | 0.86 | 0.02 |
| **50%** | 2.65 | 0.02 | 0.70 | 0.04 |
| **55%** | 2.89 | 0.05 | 0.56 | 0.05 |
| **60%** | 3.00 | 0.06 | 0.48 | 0.06 |
| **65%** | 3.04 | 0.07 | **0.45** | 0.07 |
| **70%** | 3.54 | 0.09 | **0.37** | 0.07 |
| **75%** | 3.85 | 0.12 | 0.34 | 0.09 |
| **80%** | 4.29 | 0.16 | 0.30 | 0.11 |
| **85%** | 4.65 | 0.17 | 0.26 | 0.13 |
| **90%** | 4.87 | 0.24 | 0.19 | 0.20 |
| **95%** | 6.89 | 0.29 | 0.18 | 0.28 |
| **99%** | 9.95 | 0.92 | 0.03 | 0.34 |

Source: Own creation