University College of South-Eastern Norway
Faculty - School of Business

–

Master’s Thesis in Business Administration

Study programme: Master of science and Business Administration, Business Economics

Spring 2018

Kristoffer Olstad

Exposure-Based Cash Flow at Risk:

An application to the downstream divisions of Norsk Hydro ASA

University College of Southeast Norway
Faculty of Social Sciences
Institute of Business and Administration
PO Box 235
NO-3603 Kongsberg, Norway

http://www.usn.no

This thesis is worth 30 study points

Abstract

The topic of this thesis is Exposure-Based Cash flow at Risk; a model developed to measure and explore the scenery of risk exposures associated with large firms exposed to various risks. The influence of different risk exposures fluctuations with respect to cash flow is one of the primary concerns of management in large companies. The correlation among these risk exposures, and their respective influence on a firm's cash flow, makes for a difficult scene of potential risks. Through the estimation of risk exposure sensitivities and simulation of their combined influence, this thesis calculates the potential loss in cash flow associated with fluctuations in the most significant risk exposures.

Table of Contents

Table of Tables

Table of Figures

Foreword

I would first of all like to thank my supervisor, Limei Che, for an astounding effort, brilliant insight and timely encouragement; which made this thesis feasible. In addition, I want to thank Norsk Hydro ASA for any help I have received through this period.

Hønefoss / 15.05.2018

Kristoffer Olstad

1 Introduction

The objective of this thesis is to do an Exposure-Based Cash Flow-at-Risk (EB CFaR) calculation based on the risk exposures of the cash flow sensitive divisions of Norsk Hydro ASA. EB CFaR is concerned with the downside risk of cash flow based on a firm's risk exposures and their respective fluctuations. I then conduct an analysis of the statistical properties of the regressed exposure model in addition to deriving some essential numbers with respect to the possible loss of these divisions.

The everyday operations of a firm come with an often-complex variety of risk exposures with their own volatility and respective correlations. These risk exposures bring uncertainty to the firm and management; hence, it is essential to manage and mitigate these risks. As these risks are (possibly negatively) correlated, these exposures have the potential to create natural hedges (i.e. natural risk-mitigating positions) and have a potential impact on the firm's cash flow. The summation of a firm's sensitivity to various risk exposures, and these exposures correlation with each other, makes for, at least in part, the firm's exposure to risk. In addition, a firm's positions with respect to financing and the volume of traded commodities with suppliers/customers, provide a key insight into the everyday risk assessments of the firm. Insight into the way various exposures fluctuate and the potential positions a firm could utilize in order to mitigate these exposures, is important for all firms to comprehend; making it necessary to delve into approaches that explore sceneries of various risk exposures.

The EB CFaR was developed by (Andrén, Jankensgård, & Oxelheim, 2005) as an alternative estimation of a firm's risk exposures (see section 2.2.1 for a more comprehensive description of approaches within the CFaR). Previous research with the use of EB CFaR does not amount to much, with one additional application to the UK banking sector (see Yan, Hall, & Turner, 2014). This thesis focus is on financial risk management (of risk exposures) and the fluctuations of various risk exposures that are present in every day operations; hence, the risk associated with policy and law will not be discussed.

In their attempt to develop a CFaR-approach, Andrén et al. (2005) applied this approach to Norsk Hydro ASA, a worldwide aluminium company, between 1996 and 2003 (Hydro Group then). The choice of Norsk Hydro ASA emanates from the extant research on aluminium risk management, in addition to being a well-known Norwegian company. Norsk Hydro ASA have been through various changes and has a strong competitive position, which makes it susceptible to risk and a good choice for a EB CFaR analysis. There are several different price risk exposures in producing aluminium, as found by Andrén et al. (2005), but the margins throughout the value chain differ significantly, making risk management more or less relevant depending on the respective divisions likelihood of large deficits (Hydro, 2016).

According to (Yan et al., 2014), CFaR is an alteration of **Value-at-Risk** (VaR) (see section 2.2). CFaR can be used to estimate the downside risk of more than one risk exposure. "*While VaR focuses on market risk by forecasting changes in the overall value of an asset or portfolio, CFaR is focused on variations in cash flow during a given period*" (Yan et al., 2014, p. 225).

To understand the underlying risks of one of Norway's most successful companies would be of interest for more than just Norsk Hydro ASA. Given the importance of understanding risk exposures and the multifaceted ways these risks can influence a firm's cash flow, both the firm and academics could benefit from a CFaR-calculation that lays the foundation for further investigation on the matter. Almost all firms face risk, and international firms such as Norsk Hydro do so to a higher degree than others (Bodnar, Hayt, & Marston, 1998); which implies that the knowledge of risk management obtained in this thesis could be generalizable to other firms.

2 Literature review

2.1 Previous research

Risk management has been a topic of research for a few decades, amounting to an astounding volume on various models and ways of hedging (Froot, Scharfstein, & Stein, 1993). The amount of research done with the EB CFaR approach is small compared to the related Value-at-Risk approach. Even the most recent research refers to the EB CFaR approach as a "*relatively new quantitative model*" (Yan et al., 2014, p. 225). The EB CFaR approach was developed by Andrén et al. (2005) in an attempt to complement the existing approaches of calculating CFaR, or the Cash Flow-equivalence of Value-at-Risk. They realized that the existing approaches had their respective limitations in the inclusion of market and macroeconomic risk exposures, and by extension, the ability to supply management with sufficient responses to various risks.

Andrén et al. (2005) used Hydro Group as a case and carried out an EB CFaR analysis of Hydro Groups risk exposures. Through the six-step process of calculating EB CFaR (see section 5.1 for these steps), they conducted an analysis of the three main businesses that the conglomerate consisted of in the period of 1996 to 2003. One of the significant traits of the conglomerate in this period, was the effects of "*less-than-perfect correlations*" and natural hedges. These added up to a lower risk at the Hydro Group level than the sum of the risks in the three main business areas. They found that the correlation between risk factors was generally low, implying a diversification effect, but some of the product prices did appear to correlate. The prices of the two main commodities of Hydro Group, Aluminium and Oil, had a correlation of 0.39, which was likely to have the largest bearing on the conglomerate's overall risk (Andrén et al., 2005).

Regarding the CFaR-calculation, and within a 95% confidence level, they found that the company's total cash flow would not fall short of the expected amount of NOK 13,814 million by more than NOK 2,002 million. Regarding the aluminium division, this was an expected cash flow of NOK 2,167 million with a 5^{th} percentile cash flow of 1,498 million Norwegian Krone (NOK). This implies that the CFaR amounts to NOK 669 million (2167 – 1498), which percentage wise stood for Hydro Groups largest risk, namely 31%, with Oil and energy at 16,5% and Agri at 23,7%. The overall risk for Hydro group as a whole, was at 14,6%, indicating that the composition of businesses gave a diversification effect (Andrén et al., 2005).

The continuous tasks with respect to a risk management programme are never simple and require a careful analysis of both operational and financial positions. "*Admittedly, it is difficult to carry out a cost-benefit analysis of a risk management programme by valuing potential benefits in monetary terms compatible with a firm's profit and loss statement. This difficulty is still no excuse, however, for making an opportunity cost analysis of individual cover or hedging decisions alone*" (Oxelheim & Wihlborg, 1997, p. 37). The assessments with respect to strategic alternatives in the attempt to meet a continuously developing industry, are crucial to conduct and important to comprehend.

Several studies based on surveys have examined the use of derivatives among non-financial firms (Bodnar, Hayt, & Marston, 1996; Bodnar et al., 1998; Bodnar, Hayt, Marston, & Smithson, 1995). Bodnar et al. (1998) classify financial price risk into four broad types: foreign-currency, interest-rate, commodity, and equity risk. Even though all firms are likely to face equity-risk and interest-rate risk, some firms will not face foreign exchange risk and commodity risk (Bodnar et al., 1998).

According to Bodnar et al. (1995), and with respect to the relative importance of different risk management goals, minimizing fluctuations in cash flows is the overwhelming primary objective among non-financial firms. In addition, the most frequently experienced motivation for buying into foreign currency contracts are for the hedging of contractual commitments and anticipated transactions within the year. Foreign currency hedging also functions as protection against the foreign repatriations, in other words, the stream of cash flow coming back into the country (Bodnar et al., 1995).

"*Investigating the extent and sources of foreign exchange exposure has become one of the most challenging issues in empirical international financial management*" (Hutson & Laing, 2014, p. 98). In contrast to the theory, most studies haven't found significant firm-level foreign exchange rate exposure, the so-called "*foreign exchange exposure puzzle*". Some studies (Elaine & Simon, 2009) argue that findings of significant exchange exposure would constitute evidence of inadequate hedging, and that the weak findings of previous studies could be a result of firm's rational behaviour with respect to reducing their foreign exchange rate exposure. This can happen either through financial or operational hedging, i.e. by the use of both derivatives and the location or structure of operations and the ability to modify operations in response to currency movements (Bartram & Bodnar, 2007). "*Consequently, if firms react rationally to their exposures, most firms will either have no exposure to start with, or reduce their exposure to levels that may be too small to detect empirically*" (Bartram & Bodnar, 2007, p. 660). A firms overall foreign exchange rate exposure comprises *direct* and *indirect* exposure, which arises from known and unexpected future foreign currency transactions, and from the competitive environment in which the firm operates in, respectively (Hutson & Laing, 2014). Related to this, firm size is positively correlated with foreign exchange exposure in the positively exposed firms, suggesting larger firms are exposed to a larger extent, and firms under-hedge their foreign currency positions when exact hedging is impracticable (Zhou & Wang, 2013). Large industries, as the aluminium industry, have customers that use large amounts of commodities in producing various products. The significance of the aluminium casting, extrusion and rolling business in Germany urge the question of various exposures' potential influence on cash flow generated in this country, given its significant vehicle and aviator industry.

Strategic investments and acquiring plants and factories leave firms exposed to interest rate risk as a consequence of financing operations and managing different currencies. (Bodnar et al., 1996). Haigh and Holt (2002) find that incorporating a more realistic assumption regarding the co-dependency of prices directly in to the hedging paradigm yields rewards in terms of risk reduction for traders. The last point is at least partly met by the various steps of a EB CFaR-calculation, which includes the analysis of correlations between different price risk exposures, and then, the simulations in which these co-dependencies come into play.

2.2 The measurement of risk exposures – GARCH, VaR and CFaR

"*The standard approach of measuring exposure to underlying sources of risk is to regress investment returns on risk factors that proxy for different trading strategies*" (Bollen & Whaley, 2009, p. 1031). The regression method examines how the unhedged cash flow of the firm performed historically in relation to a risk factor. More specifically, this method estimates the factor betas as slope coefficients from regressions of historical returns or cash flow on the risk factor (Hillier, Grinblatt, & Titman, 2012).

Variance measures average risk only and does not distinguish between specific parts of a return distribution such as the tail of the distribution. "*A shortcoming of the variance risk measures is that it cannot distinguish between positive and negative returns and, therefore, it does not allow for distribution asymmetries*" (Cotter & Hanly, 2012, p. 135). According to Cotter and Hanly (2012), two broad approaches have emerged in the attempt to address these issues, Value-at-Risk (VaR) and generalized autoregressive conditional heteroskedasticity (GARCH).

VaR is perhaps the most popular way to measure risk exposure, a measure of loss associated with rare or extraordinary event; such as the value of derivatives, which is determined by fluctuations in the underlying asset (Hillier et al., 2012). VaR is a simple concept that effectively quantifies market risk, and for this reason, a commonly used tool (Chuang, Wang, Yeh, & Chuang, 2015). In 1993, JP Morgan pioneered VaR as a measurement of downside risk for any portfolio or financial institution (Yan et al., 2014); and is determined by the time interval under consideration, as well as by what the manager regards as normal market conditions. This implies that, the smaller a manager's propensity to ignore losses is, the higher the estimate of VaR will be (Hillier et al., 2012). An example of a VaR-estimation is the weekend volatility effect regarding the market for gold futures at the Chicago Mercantile Exchange, as Huldeborg (2013) did in her thesis. In cases where VaR is applied to non-financial firms, it will only capture a small part of the total exposure on the basis that it ignores the underlying commercial cash flow (Andrén et al., 2005). Through the years, several financial firms have developed measures of VaR in order to allocate capital or monitor market risk limits, but these have some limitations that, in some cases, make other measures like CFaR more applicable. When Yan et al. (2014) estimated liquidity risk using the EB CFaR-approach, their argument was that, since liquidity depends on several different risk exposures, VaR, as a measure of risk, would not fully reflect the volatility of cash flow (Yan et al., 2014).

2.2.1 Value-at-Risk vs. Cash Flow-at-Risk

It should be evident that there is a difference between VaR and CFaR (Yan et al., 2014). For instance, if the VaR on an asset is €50 million at a 1-week time interval, 95 % confidence level, then there is only a 5% chance that the value of the asset will drop by more than €50 million over any given week. With this in mind, it has the intuitive interpretation of the amount of economic capital that must be held to support that level of risky business. A similar interpretation could come out of a CFaR of €50 million with 95% confidence level, which can be explained as there being only a 5% probability that cash flows will drop by more than €50 million during the next week (Yan et al. 2014). Similar to Andrén et al. (2005), but in contrast to Yan et al. (2014) use of annual data, this thesis will use quarterly data on EBITDA as a measure of cash flow. The CFaR calculation would therefore concern the quarterly "cash flow" for a case firm, or specific divisions thereof.

"*Cash flow-at-Risk is gaining in popularity among industrial companies for easily summing up all of their risk exposures in a single number that directly reflects the firm's risk tolerance*" (Yan et al., 2014, p. 227). A required component in the calculation of risk statistics, such as CFaR, is an estimate of the probability distribution of cash flow at some future point in time. According to Andrén et al. (2005), there are two dominating approaches to estimate the probability distribution, with their respective advantages and disadvantages. "*The two most popular approaches to calculating CFaR – bottom-up and top-down – tend to focus either on cash flow conditional on market changes or on total variability, with little attempt to isolate specific exposures*" (Andrén et al., 2005, p. 86).

(RiskMetrics, 1999), that originally developed CFaR, relies on a "bottom-up" approach that attempts to identify both cash flow components and their exposure to market risk. This approach requires specified levels of market risk, and by extension, the cash flow volatility is conditional on these specified market risks. In case it is not possible to identify all sources of exposure to market risk, a firm's total exposure is more accurately measured by its cash flow "delta", or its cash flows sensitivity to an incremental change in the underlying market price (Andrén et al., 2005). "*The basic assumption of the this* (bottom-up) *approach is that there is a direct link between production prices and exchange rates on the one hand and cash flow on the* *other*" (Yan et al., 2014, p. 227). The findings of more than 20 years of research (through Oxelheim & Wihlborg, 1987, 1997, 2005) on macroeconomic and market risk contradicts this assumption. Because total corporate risk exposures are so complex and multifaceted, it would be dangerous to use pro forma statements. Andrén et al. (2005) believes that the use of pro forma statements, in modelling risk exposures, would yield biased results because of its inability to deal with more than one exposure at a time. Even if such complex relationships are reflected through modelling risk exposures, this type of modelling have a tendency to ignore the simultaneous impact of exchange rates and the effects of other macroeconomic market variables (Yan et al., 2014). "*The bottom line is that while one can attempt to implement a bottom-up CFaR analogue to companies like dell, there is a danger that such an approach will simply leave out some important sources of risk, badly mis-measure others, and thus lead to a highly inaccurate estimate of overall CFaR*" (Stein, Usher, LaGattuta, & Youngen, 2001, p. 101).

The "top-down" approach was developed by Stein et al. (2001), which focus on the overall cash flow volatility. In contrast to the "bottom up" approach, the "top down" approach pools cash flow data for a large number of comparable companies to estimate a pooled cash flow distribution (Andrén et al., 2005). "*We use a relatively sophisticated benchmarking technique to find the best comparables for a given target company, searching for those other companies that most closely resemble our target on four dimensions: (1) market capitalization, (2) profitability, (3) industry riskiness, and (4) stock price volatility*" (Stein et al., 2001, p.101). With this approach comes the advantage of an historical average exposure estimate that reflects a number of firm's collective experience of a variety of market conditions. An apparent limit to this approach is the fact that a specified firm may or may not be anything like the average company in the sample, nor the specific sample group it is compared with. In addition, CFaR estimated with a “top down” approach does not provide an estimation conditioned on market risk and does not easily encompass this type of risk exposure (Yan et al., 2014).

Given the limitations of the two approaches mentioned above, Andrén et al. (2005) advocates the use of a third approach, namely “*Exposure-Based Cash Flow-at-Risk*”. This approach can be used to calculate both the overall CFaR and its conditioned CFaR with respect to macroeconomic and market risks. “*The exposure-based cash flow at risk model, involving a process of mapping out the firm’s exposures and the asking of difficult questions about how and through what channels the firm’s cash flow is exposed to risk, is one of the key benefits of having a risk management programme*” (Yan et al., 2014, p. 228). Yan et al. (2014) use an exposure-based CFaR model to measure UK banks’ downside liquidity risk, and with an emphasis on a careful analysis of the drivers of corporate macroeconomic exposure. Step three of the CFaR-calculation implies (Andrén et al., 2005) (see section 5.1), the estimation of exposure coefficients, or sensitivity coefficients, should be derived as beta coefficient. The main advantage of this particular measure of exposure is that it includes commercial price and quantity effects, in addition to valuation effects (Oxelheim & Wihlborg, 1997). In contrast to the top-down approach, the EB CFaR-model of the company’s risk exposures provides management a set of sensitivity coefficients that are able to explain the variability in EBITDA as a function of various risks (Andrén et al., 2005).

2.2.2 The framework of EB CFaR

Through the development of EB CFaR, Andrén et al. (2005) derived a 6-step process, of which is discussed in the methodology chapter.

2.2.3 The possible insights of EB CFaR

EB CFaR opens up rich possibilities for decomposing the final CFaR estimate into one or a group of related risk exposures. Andrén et al. (2005) argue that EB CFaR provides insight into the cash flow dynamics of the company and the respective key drivers of risk. The method makes for the potential clarification of the portfolio aspects of corporate risk, which comes with considerations on three levels (Andrén et al., 2005, p. 84):

(1) There may be exposures that offset each other, in other words, a company's positions may amount to natural hedges.

(2) The (simulated) error terms in the regressions – which reflect cash flow changes independent of the risk factors – could be correlated across business areas. In case a conglomerate's divisions error terms are correlated, this could indicate a tendency for macro-independent changes to be systematic across business areas.

(3) There could be a portfolio effect from exposures to correlated risk factors. "*A high correlation between two risk factors will have an impact on estimated CFaR, and the sign of the exposure coefficients determines whether the overall net impact is positive or negative*" (Andrén et al., 2005, p. 84). As a consequence of this and in case two factors are positively correlated, but a company exposure to these factors are opposites, there is a dampening effect on cash flow at risk.

In addition to the previous insights that comes from taking a portfolio view, it is not always necessary to include all product prices in the exposure model. In the case of Hydro Group between 1996-2003, the inclusion of ammonia alone seemed sufficient to capture the entire price risk exposure of the fertilizer business (Andrén et al., 2005).

2.3 Price volatility of commodities

"*Commodity markets have experienced dramatic up-and-down movements recently within a relatively short period of time*" (Casassus, Liu, & Tang, 2012, p. 1324). Casassus et al. (2012) mentions the movements of crude oil from January of 2007 ($50) through July of 2008 ($145), and then five months later, when the price was down to $30 per barrel of oil. With industrial metals being another example of commodities that have experienced similar patterns. Price volatility is one of the risk exposures present in the trading of commodities, and because of this, one of the reasons why corporations might use derivatives to lower their exposure to price variations (Bodnar et al., 1996).

In some industries, production depends on large amounts of different commodities, as it is with the aluminium industry; see figure 1 (p. 30) for a brief description of inputs. Chng (2009) argue that modelling optimal hedge ratios on a commodity-by-commodity basis produces hedging errors; but ask whether these conceptual hedging errors are relevant with respect to other ways of reducing financial losses. It would, in case they are, be an empirical question (Chng, 2009). The findings of Dutta & Hasib Noor (2017) suggest that policy-makers should consider the impact of oil price uncertainty on the hedging of both metal and non-energy aggregate markets; as these industries production depends largely on the crude oil market. As for the case firm, they are not directly exposed to volatility in the marker for crude oil, rather, this is a relatively small expense in the mining of bauxite. In addition, the nature of a CFaR-analysis will most often give a comprehensive description of various exposures that comes as a consequence of a firm's operations, which could give some insight relative to the findings of Dutta & Hasib Noor (2017). According to several studies, acquiring commodity futures contracts can function as excellent portfolio diversifiers and for some, and effective in hedging inflation (Bodie, 1983; Bodie & Rosansky, 1980). As for the aluminium industry, there are a few well known exchanges for metals, which also functions as markets for aluminium futures. In the management of aluminium price risk, futures contracts are often entered in response to the various physical contracts of aluminium delivery (Hydro, 2016).

In line with economic portfolio theory and the findings of Andrén et al. (2005) and Oxelheim and Wihlborg (1997), positions that have insignificant correlations with each other tend to mitigate the risk. It would be interesting to see if the estimated impact of various risk exposures and their respective correlations amount to the same, for the case firm, as they did in the period of Andrén et al. (2005) study, i.e. 1996-2003.

2.4 Hedging Performance

Hedging performance is reflected through the hedge fund managers ability to change asset classes, strategies, and leverage in response to changing market conditions and arbitrage opportunities (Bollen & Whaley, 2009). Hedging performance comes from the ability to shift ones' investments as shifts in macroeconomic factors happens. This was examined by Bollen and Whaley (2009) through applying a changepoint regression to a sample of live and dead funds during a given period. They found that if there are significant changes in risk factor parameters, the alphas from a constant parameter regression will be misleading measures of abnormal performance (Bollen & Whaley, 2009). Since their research is among financial firms, that primarily profit from value-based investments, the hedging performance in the case of non-financial firms would play out in a different way. For instance, the role of financial and operating hedging would play their respective roles in mitigating the risks associated with the operations of a firm. The description of the case firm's risk management regarding the various risk exposures give some insight into the choices they have. FASB's (Financial Accounting Standards Board) statement No. 133, "*Accounting for Derivative Instruments and Hedging*

Activities" requires some significant changes to the way derivatives are measured and reported in the firm`s financial statements. It also provides official recognition of the use of a broader array of derivatives in hedging transactions (Bodnar et al., 1998). Hedging performance would be difficult to measure in terms of specific responses to changes in macroeconomic and market, but the results of a CFaR-calculation could give some understanding of the extent of a firm's exposure to specific changes. There is also an important distinction between being exposed to a given risk exposure, and the extent this exposure could influence the firm's cash flow, as argued by Andrén et al. (2005).

2.5 The MUST-framework.

The MUST-framework is an abbreviation for the macroeconomic uncertainty strategy analysis. This framework is developed through the work of Oxelheim & Wihlborg (Oxelheim & Wihlborg, 1987, 1997, 2005) and consists of three publications that give managers and organizations a basis for understanding their own positions, how to assess macroeconomic uncertainty, fluctuations and corporate performance.

Andrén et al. (2005) did a relatively small example out of Hydro Group between 1996-2003, giving a basis for the risk exposures of the following estimations. "*Though the channels may differ, all firms are inevitably exposed to the shocks and disturbances of a global marketplace*" (Oxelheim & Wihlborg, 1997, p. 1). Oxelheim and Wihlborg (1997) argue that in spite of the complexity of relationships in the macroeconomic environment, the important effects on the firm's performance can indeed be captured by the analysis of a limited number of variables. The four main exposures that are emphasised by Oxelheim and Wihlborg (1997) are exchange rates, inflation rates, interest rates and relative prices; which resemble the findings of the survey study of Bodnar et al. (1995). In the case of the aluminium industry, it is important to distinguish between macroeconomic exposures and firm-/industry specific shocks. "*The relationships among exchange rates, inflation rates, and interest rates are often discussed by academics in terms of market equilibrium relations among the variables and deviations from these relations*" (Oxelheim & Wihlborg, 1997, p. 10). Although the equilibriums should be found in the presence of assumptions, there is a great deal of inference which contributes to deviations from these equilibrium relationships (Oxelheim & Wihlborg, 1997). Therefore, and according to Oxelheim & Wihlborg (1997), a firm have every reason to formulate an explicit policy with respect to the risks and/or opportunities they create. In general, many exchange rates move together, which is also the case for interest rates and inflation rates. Andrén et al. (2005) focused on three long term Government Bonds (10 year).

The MUST framework distinguishes between three sets of factors that determine a firm's exposure; First, the macroeconomic structure through capital mobility and the velocity of price adjustments; secondly, the policy regime set by financial authorities influence the degree to which variables adjust to disturbances and with what time lag the adjustment occurs; and then thirdly, the sensitivity of a firm's value (or cash flow) to changes in macroeconomic conditions depends on firm-specific positions with respect to the respective markets for inputs and outputs. Regarding these three sets of factors, the third is of upmost importance in managing a firm's respective risk exposures, and with respect to an EB CFaR calculation.

"*The concept of risk refers in general to the magnitude and likelihood of unanticipated changes that have an impact on a firm's cash flows, value or profitability*" (Oxelheim & Wihlborg, 1997, p. 17). It is often made a distinction between "downside" and "upside" risk; which refers to the probability of unanticipated outcomes below or above the expected outcome, respectively (Oxelheim & Wihlborg, 1997). CFaR is concerned with the downside risk and involves an estimation of this within a specified level of statistical confidence (Andrén et al., 2005). According to Oxelheim and Wihlborg (1997), the primary risk for a non-financial firm would come from its commercial risk – in other words – its uncertainty about the value of cash flow that can be generated by its physical assets producing output. Within the MUST-framework, the focus is on the primary or commercial risk of a non-financial firm's business operations, in addition to the firm's composition of liabilities that are important because they can be used to balance out commercial risk.

2.5.1 Macroeconomic risk

Oxelheim and Whilborg (1997) use three classifications to describe risks in the macroeconomic environment, which captures the basic point that all firms are exposed to macroeconomic risk. The classifications are:

(1) Interest rate risk: which should be considered when measuring exposure to interest rate changes.

(2) Currency risk: with a distinction between (real) exchange rate risk and inflation risk.

(3) Country risk: considers the probability and magnitude of unanticipated changes in a country's productive development.

The three could be distinguished from commercial risk which refers to the likelihood and magnitude of unanticipated changes in firm-specific in addition to industry-specific prices and demand conditions. In most cases, the presence of interdependency arises because different variables adjust simultaneously to shocks happening to the economy (Oxelheim & Wihlborg, 1997).

2.5.2 Cash flow exposure

Andrén et al. (2005) followed the steps of MUST-analysis (Oxelheim & Wihlborg, 1987, 1997, 2005), which defined exposure as *"the sensitivity of cash flow to changes in different macroeconomic variables*" (Oxelheim and Wihlborg, 1997, p. 95). This measure (squared) multiplied by the variance of the exchange rate gives us the contribution of the respective risk exposure to the variance of cash flows. In some circumstances, this measure has a couple of drawbacks:

- The measure may provide strongly misleading impression of exposure if related variables are disregarded in terms of their influence. Such as exchange rate exposure without the inclusion of inflation rate and interest rate.
- If the historical data on the exposure seems to be unstable, then the exposure coefficients obtained may not represent a good measure for the future.

In the case of exchange rate and interest rates, Oxelheim and Wihlborg (1997) expects that these are correlated, making these exposures partly overlapping. To resolve the problem of overlapping, the exposure coefficients should be estimated using a multiple regression of the cash flow on the exchange rate and variables suspected of being correlated.

2.5.3 Commodity price risk exposure

Andrén et al. (2005) came to see the aluminium price and oil price as the most dominating exposures. In the 1996 – 2003 period, Hydro Group's Aluminium division were only partly integrated throughout the value chain, which is not the case today (see ch. 4).

2.5.4 Exchange rate risk exposure

As Andrén et al. (2005) found, both U.S. Dollar and Euro are significant in terms of exchange rate risk. The denomination of aluminium prices in U.S. Dollar and the significance of the European market, in addition to Hydro's invoice currency of Euro, makes the both of them essential with respect to the value of earnings in Norwegian Krone (Andrén et al., 2005). Andrén et al. (2005) included the exchange rates of NOK/ USD and that of NOK/EURO.

2.5.5 Inflation rate risk exposure

"*The importance of exchange rate risk to competitiveness is also determined by inflation differentials*" (Andrén et al. 2005, p.81). In case exchange rate changes are completely offset by inflation differentials, exchange rates cannot influence competitiveness. Further, Andrén et al. (2005) recognized that the aluminium division in particular had the conditions for this type of exposure. Aluminium is said to be pro-cyclical (Andrén et al. 2005), in other words, the quantity of aluminium sold is related to economic fluctuations.

All in all, Andrén et al. (2005) identified four sources of inflation risk; Norwegian, the European Union and the U.S. inflation rates.

2.5.6 Interest rate risk exposure

"*Interest rates can have an effect in operating cash flow to the extent demand in an industry is sensitive to the cost of capita*l" (Andrén et al., 2005, p. 81). As many of the buyers of refined aluminium products are capital-intense industries, the long-term interest rates of both Europe and U.S. could be significant commercial interest rate risk exposures. The use of EBITDA as a measure of cash flow effectively excludes a firm's own exposure to interest rates (Andrén et al., 2005; Stein et al., 2001). In summation, the Norwegian, German and U.S. 10-Year Government Bonds would be the long-term measures of interest rates (Andrén et al. 2005).

3 Research question with underlying questions.

Research on risk management and hedging of risk exposures rests, in general, on the implications of capital market imperfections (Froot et al., 1993). An extension of this implies that firms, with possible gains through hedging, have incentives to actively search for and utilize investments, operational positions and active trading of different derivatives; which some surveys studies (e.g., Bodnar et al., 1996, 1998; Bodnar et al., 1995) gave some good insight into among American non-financial businesses.

The Value-at-Risk measure and its usefulness among financial institutions (Yan et al., 2014) raise the question of whether non-financial firms should, and could, develop instruments to advance their understanding of exposures potential impact on their cash flow. Andrén et al. (2005) and Oxelheim and Wihlborg (1987, 1997, 2005) suggest that the possible natural hedges that arise from a firm's positions (i.e. financial and operational) should be assessed as a part of their risk management plan. The steadily growing international industries are exposed to several kinds of risks, making it essential for both firms and academics to comprehend the complex composition of these risks. As stated by Oxelheim and Wihlborg (1997), it is difficult to make these calculations, but that does not mean one should hesitate to comprehend these kinds of multifaceted exposures.

As large companies specialize, demerges and develop their operations in the attempt to gain competitive advantages, these strategic choices lead to an array of risk exposures and, as Andrén et al. (2005) found, diversifying composition of divisions. In the attempt to mitigate risks, and recognize these in an evolving industry, firms have to meet changes with a new and updated understanding of the degree to which they are exposed. In contrast to the two other Cash Flow-at-Risk approaches, bottom-up and top-down, the Exposure-Based approach makes it possible to give some firm specific insights into divisions separate cash flows. In applying the framework to a case firm, the divisions of interest would be those of lowest margins.

As section 4 will describe, Norsk Hydro ASA, the case firm of Andrén et al. (2005) have been through various changes that makes it a good choice for analysing their EB CFaR. The competitiveness of the aluminium industry has required competitors to position themselves in the attempt to secure access to raw materials and effective ways of delivering products to the larger markets.

This thesis' objective is to do an Exposure-Based Cash Flow-at-Risk calculation for Hydro's aluminium processing divisions; i.e. the sale of premium aluminium in addition to casting, extrusion and rolling of aluminium generates a certain amount of their cash flow; associated with the smaller margins with respect to first part of the value chain (see figure 1 p.30), and therefore, the larger amount of risk. The research question of this thesis comes as a result of the need for complementing the understanding of risk exposures that surrounds highly cash flow-sensitive divisions. Using quarterly data on relevant risk exposures in the period of 2007 to 2016, the question of research emanates as follows:

- How does the Exposure-Based Cash Flow-at-Risk to Norsk Hydro ASA's most Cash Flow-sensitive divisions appear today?
- Do the finalized exposure models comply with the statistical properties emphasised by Andrén et al?
- What would a simulation of these risks amount to in terms of Cash Flow – at – Risk?

4 Norsk Hydro ASA

Since the production of fertilizers started in 1903, Norsk Hydro have been going into energy intensive businesses, and their strategic choices have often been influenced by the potential for relatively cheap and stable sources of energy (Hydro, 2018a).

It was not until 1 September 1986 that Hydro Aluminium was formed through the integration of Årdal and Sunndal Verk (ÅSV) and Hydro's aluminium division. This new company had a large and strong production base in Norway and had a clear international profile. Together, they became more effective than they had been as competitors (Hydro, 2018b).

In 1999, Hydro presented a new strategy and goal of building a global position within Oil and Energy, Aluminium and Agriculture (Hydro, 2018c). With the three core divisions came a variety of different risk exposures, and Andrén et al. (2005) conducted a EB CFaR-calculation based on these three divisions of Hydro Group; which was the topic of section 2.1.

Through the years, Germany industry have been one of the largest consumers of aluminium, with 15,3% of Norsk Hydro ASA's operating revenue coming from this country in 2016 (Hydro, 2016, p. 4). In 2002, Hydro Aluminium acquired the German aluminium company Vereinigte Aluminiumwerke AG (VAW), which had a strong position in rolling mills and cast products for the automotive industry. The increasingly global aluminium market together with the expansions of Alcoa, Alcan and Pechiney's (three of the main competitors) portfolios of business, made it necessary for Hydro Aluminium to acquire a well-run aluminium company with a strong position within the automotive- industry, given the relatively stable and diversified demand for various vehicles (Hydro, 2018d). Through the takeover of VAW, Hydro became the largest aluminium company in Europe and had come full circle (Hydro, 2018e).

"*In 2007, Hydro's oil and gas businesses spun off and merged with Statoil*" (Hydro, 2018f). In line with the strategic path that the board of Hydro decided to pursue in the early nineties, the oil division of Hydro merged off with Statoil in 2007. A few years earlier, the fertilizers division of Hydro demerged into YARA, a world leading producer of agriculture products, implying that Norsk Hydro ASA had become an integrated energy and aluminium company.

In 2011, Hydro took over the bauxite mining activities of Vale in Para, Brazil. With this takeover, Hydro became a full circle aluminium company with activities throughout the entire value chain (see figure 1, p.30) (Hydro, 2018g).

Sapa was Hydro's largest competitor in the production of aluminium extrusions, Hydro's extrusion division merged in 2013, giving Hydro a 50 percent interest. The new Sapa became a world leading company in processing tailored extrusions in the European home market as well as in the U.S., South America, China, India and Vietnam (Hydro, 2018h). The fifty/fifty ownership lasted until 2017, when Hydro acquired Sapa and became the sole owner of over 100 manufacturing facilities (Hydro, 2018i).

4.1 The structure of Norsk Hydro ASA

The structure of Hydro Group in the period of 1996-2003 (the period chosen by Andrén et al., 2005) had an entirely different composition than what we see today. What remains is a specialized aluminium company with its own production of hydroelectric power and participation throughout the whole value chain from mining of bauxite and alumina, production of primary aluminium and then casting, extrusion and rolling of aluminium. The selling of primary aluminium in addition to casting-, extrusion- and rolling of aluminium resembles a downstream business; and is the main focus of this thesis.

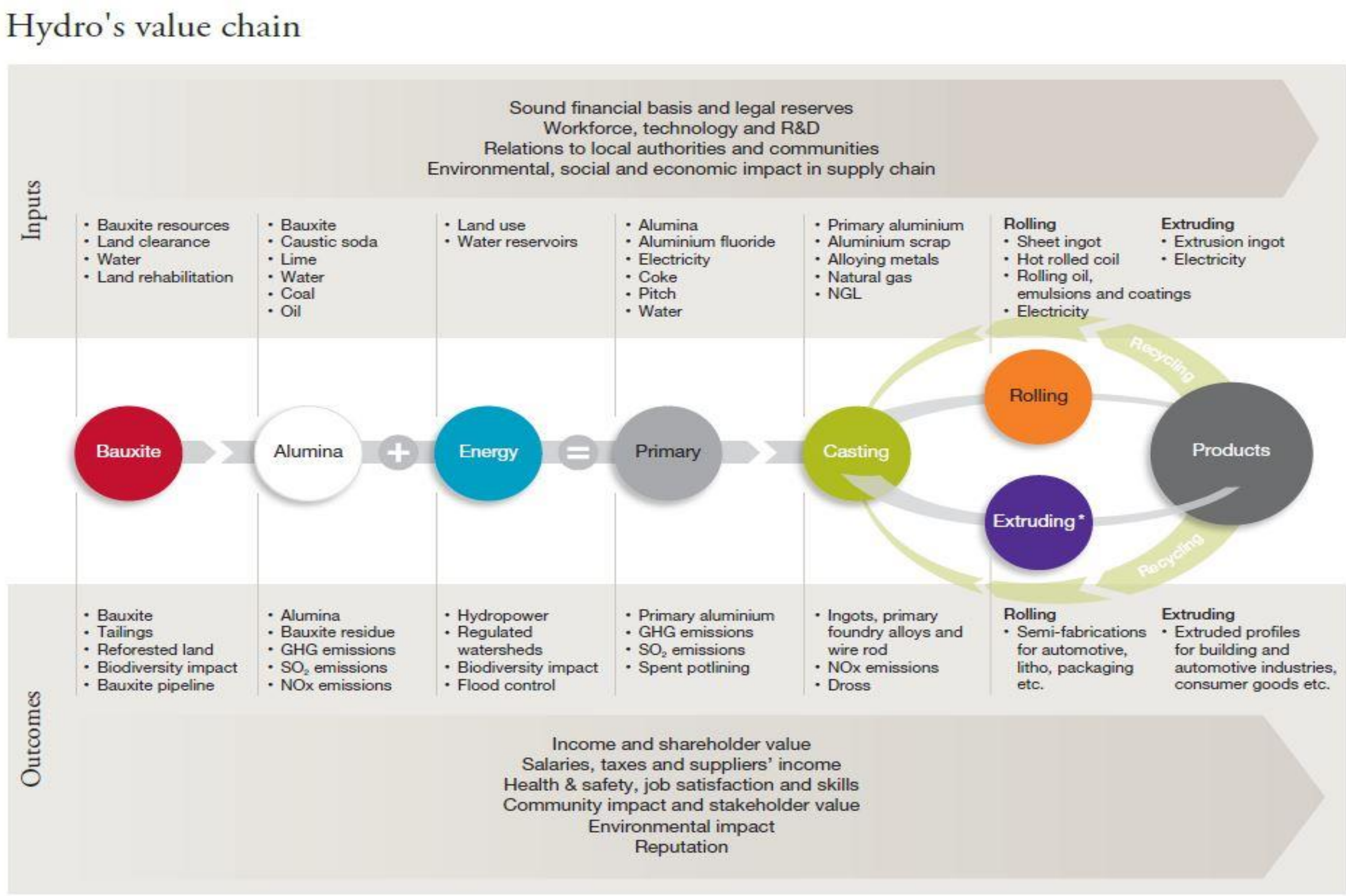


Figure 1: Value chain of Norsk Hydro ASA

4.2 Risk Management – Norsk Hydro ASA

"*Hydro's integrated value chain plays å key role in mitigating risk as the earnings volatility in upstream aluminium is typically higher, whereas downstream and Energy business generate more stable earnings over time*" (Hydro, 2016, p. 20). Note 12 in the annual report for 2016 states that risk exposures are evaluated based on a holistic approach, that is, offsetting positions are pursued and taken advantage of in case these positions are possible and economically viable (Hydro, 2016, pp. F31 - F33).

Hydro's total production of primary aluminium in 2016 amounted to 2085 (kilo metric tonnes) (Hydro, 2016, p. 17). The hedging of aluminium price risk is done through the utilization of futures contracts on the London Metal Exchange (LME); mainly for two reasons. (1) achieving an average LME aluminium price on smelter production, and (2) because the sale of aluminium products is based on margins above the LME price, the entering of customer and supplier contracts are met with corresponding physical or derivative future contracts at fixed prices. The sale of primary aluminium includes a premium in addition to the LME aluminium price. These premiums, and the pricing of, can be volatile and varies with physical demand and supply, with regional and product-related differences. In recent years, these premiums have accounted for a higher share of the revenue than historic averages (Hydro, 2016).

Hydro's consumption of electrical power is, in large, secured through long-term contracts with power suppliers and through Hydro's own production in Norway (Hydro, 2016).

"*On average the US dollar strengthened against the Norwegian kroner and Brazilian real, benefiting the company's competitive position*" (Hydro, 2016, p. 13). Hydro's primary foreign currency risk is linked to fluctuations in the value of the US dollar versus the currencies in which significant costs are incurred. In addition to this, the annual report of 2016 states that results and equity are influenced by value changes for the functional currencies of the individual entities and the NOK as Norsk Hydro's presentation currency. The quote above implies that an average strengthening of the U.S. dollar to that of Norwegian krone and Euro, leads to a benefit with respect to Hydro's competitive position. Given the significance of the US dollar exposure, Hydro's policy is to raise funding primarily in US dollar in the attempt to mitigate this exposure. Furher, they use foreign currency swaps and forward currency contracts in addition to funding in US dollar (annual report 2016, p. F32).

Uncertainty or risk of significant cash payments or margin calls related to derivative instruments is limited due to strict volume limits, value-at-risk and tenor limits for relevant trading activities (Hydro, 2016).

5 Methodology

This chapter gives a detailed description of an Exposure Based Cash Flow-at-Risk (EB CFaR) calculation of Hydro's downstream business, i.e., the selling of primary aluminium plus casting-, extrusion- and rolling of aluminium. What follows is a description of the EB CFaR-framework, the different data, the exposure model and then the simulation method.

5.1 The framework of Exposure-Based Cash Flow-at-Risk

The calculation of Cash flow-at-Risk have to be measured with a relevant target variable. The total variability of cash flow can be attributed to the fluctuations of significant factors, which are independent of changes in EBITDA. The six steps of a EB CFaR are as follows (Andrén et al., 2005, pp. 79 - 80):

1) Identify macroeconomic and market variables expected to be significant to the firm's cash flow by investigating the competitive environment, the firms (and its major competitors) cost structures, and the price and wealth sensitivity of its customers.
2) Acquire or generate forecasts of the identified macroeconomic and market variables.
3) Estimate the exposure model. This model must both have a plausible economic theory behind it and good statistical properties (high explanatory value, statistical significance, and well-behaved error terms).
4) Simulate values of the macroeconomic and market variables by randomly selecting observations from their mean/correlation matrix (using, for example, 10 000 Monte Carlo simulations); with a randomly drawn value for the error term in each simulation.
5) Insert the simulated values in the exposure model to derive both a conditional distribution of cash flow – that is, conditional on macroeconomic and market volatility – and a distribution of cash flow that reflects all other non-macroeconomic sources of volatility – that is, the error term.
6) Combine the two cash flow distributions, determine the target confidence level, and then calculate the (EB) CFaR.

Andrén et al. (2005) recommend that one should implement a framework of that like MUST, developed through years of studying macroeconomic and market exposures by Oxelheim and Wihlborg (Oxelheim & Wihlborg, 1987, 1997, 2005).

If the error term is well behaved, it has by definition no correlation with any of the explanatory variables or its own past values; and one can simply draw a value from a normal distribution $(N \sim [0, \sigma^2])$ and add that value to the conditional distribution (Andrén et al., 2005).

5.2 Data and variables

The application of EB CFaR require a sample of a few years with observations in order to derive significant estimations of exposure, where the inclusion of high risk periods gives the opportunity to assess financially rare events. In addition, the operations of a firm should be stable and without big changes, hence, the period chosen for analysis is 2007 – 2016. Collecting quarterly data from the start of 2007 gives the opportunity to capture the high risk in the financial crisis in 2008-2009, which could be considered as extreme events relative to the years considered normal. Considering the case of Norsk Hydro ASA, the set of data will consist of relevant market- and macroeconomic variables. These variables include quarterly average prices and exchange rates in addition to other macroeconomic variables (Andrén et al., 2005; Yan et al., 2014). The quarterly data frequency for the sample period between 2007 and 2016 provides a sample of 40 observations. Some of the problems with the data include a limited number of observations (40), similar measures of inflation and interest rates in 3 geographical areas, i.e. United states, Europe(Germany) and Norway; in addition to a cumulated measure of earnings or EBITDA (i.e. adding up 4 division’s earnings).

The estimation of sensitivity-betas requires enough observations and the use of quarterly data is beneficial in that it is the most frequently published with respect to earnings among international firms (Andrén et al., 2005). In case observations of the independent variables have not been available quarterly data (i.e. daily, weekly, monthly), then quarterly averages have been calculated.

5.2.1 Data on dependent and independent variables

Data on EBITDA from the quarterly financial reports was collected (Hydro, 2018j). The use of EBITDA is in line with what Stein et al. (2001) did in their study and gives an accurate and reliable source of cash flow. Because Norsk Hydro ASA experience most of their risk in the second part of the value chain (see figure 1 p.30), the EBITDA-numbers included will be those related to selling primary aluminium, plus casting-, extrusion- and rolling of aluminium. In every quarterly report, there is a – "*Operating segment information*" – note, from which the data on EBITDA is gathered.

Quarterly data on the aluminium prices from Quandle (Quandl, 2018) is available back to 2012, making it necessary to collect data from another database. Norsk Hydro ASA was contacted to get hold of the relevant data from year 2007 throughout 2011, which they got from Reuters, a financial service provider.

Exchange rates are a significant risk exposure, as found by Andrén et al. (2005). The quarterly data on the NOK/USD and NOK/EURO exchange rates were available as monthly data from the Norwegian Bank (NorgesBank, 2018); making it necessary to calculate quarterly averages as the applicable form of data.

Inflation rates gives an indication of the price development in a country or a larger region. It is an essential part of the CFaR-calculation on the basis that is could explain some of the variation in Norsk Hydro ASA's EBITDA. Andrén et el. (2005) made the case for the inclusion the inflation rates of the U.S.-, European and Norwegian. Data were gathered from Trading economics (TradingEconomics, 2018).

Andrén et al. (2005) realized that long-term interest rates were of great significance for Norsk Hydro ASA's customers, who area capital-intensive industries. Data on 10-year government bonds for Norway (i_{nor}), Germany (i_{ger}) and the United states of America ($i_{U.S.}$) were gathered from trading economics (TradingEconomics, 2018).

Given that Norsk Hydro ASA acquired the German company VAW in 2002, the electricity price of Germany is of interest given that the aluminium industry is energy intensive. The prices from the German electricity market on Rolling Contracts was acquired through Hydro and Reuters financial services. Note 12 in the annual report of Norsk Hydro ASA states that is a part of Hydro's risk management to hedge the price risk of electricity with long term contracts. Even though the realized electricity price is impossible to come by, the use of data on rolling contracts makes it possible to regress the influence of the German electricity price. Table 1 presents the definitions of all the variables and the data sources.

Table 1: Description of variables and sources of data

Variable	Definition	Source
EBITDA	Earnings Before Interest, taxes, depreciation and Amortization	Norsk Hydro ASA
P_{alu}	LME - Dollar Price per metric tonne, Cash Ask (official)	Quandl / Reuters
P_{el}	Rollover Rolling Contracts, Euro / Megawatt-hour, i.e. €/MWh	Reuters
$S_{NOK/\$}$	Norwegian Krone / U.S. Dollar exchange rate spot price	Norges Bank
$S_{NOK/€}$	Norwegian Krone / EURO exchange rate spot price	Norges Bank
i_{nor}	Norwegian 10-year Government Bond	TradingEconomics
π_{nor}	Norwegian inflation rate	TradingEconomics
i_{ger}	German 10-year Government Bond	TradingEconomics
π_{euro}	European inflation rate	TradingEconomics
$i_{u.s.}$	United states 10-year Government Bond	TradingEconomics
$\pi_{U.S}$	United states inflation rate	TradingEconomics
PAS	Premium Aluminium Sold in metric tonnes (Control variable)	Norsk Hydro ASA

5.3 Exposure-based model

EB CFaR involves the estimation of exposure coefficients (deltas) that provide information about how various macroeconomic and market variables are expected to affect the company's cash flow (Yan et al., 2014). Andrén et al. (2005) argues that these coefficients can be estimated through the use of a multivariate regression framework for analyzing corporate exposures to macroeconomic and market risk exposures. This approach recognizes the interdependence of such exposures. The exposure model is a multivariate regression that comprises of relevant macro and market variables on Hydro's quarterly EBITDA, and is based on the work of Oxelheim and Wihlborg (1997). The model is presented as follows:

$$CF_t^{DC} - E_{t-1}[CF_t^{DC}] = \beta_0 + \sum_{i=1}^{n} \beta_i \left(X_{it} - E_{t-1}(X_t)\right) + \varepsilon_t$$

Where CF_t^{DC} is the cash flow (EBITDA) in domestic currency in period t, and $X_t = [P_{alu}, P_{el}, S_{NOK/USD}, S_{NOK/EURO}, i_{Nor}, i_{U.S.}, i_{Ger}, \pi_{Nor}, \pi_{Euro}, \pi_{U.S.}, PAS]$ the macroeconomic and market variables include a measure of inflation (π), spot exchange rates ($S^{DC/FC}$), interest rates (i), and a key commodity price (aluminium (P_{alu}) , electricity (P_{el})). *"Because risk derives from random, unexpected deviations from forecasts, expected or forecasted values are included to capture forecasted or expected developments of the market variables in each period"* (Andrén et al., 2005, p. 79). This is done through $(-E_{t-1}[CF_t^{DC}])$ and $(-E_{t-1}(X_t)$, which captures the cash flow and macro-/market variable's unexpected deviations in each period, respectively. As mentioned, it is assumed that all variables included follow random walks, which implies that all changes are unexpected. The Martingale model principle implies that the information t-1 needed for a rational expectation of the value of price at time t is already contained in price at t-1 (Yan et al., 2014). Therefore, we can get:

$$\mathrm{E}(CF_t) = CF_{t-1}^{DC}$$

And

$$\mathrm{E}(X_t) = X_{t-1}$$

Following Yan et al. (2014), the reduced form of the exposure Cash flow model can be interpreted as follows:

$$\Delta CF_t^{DC} = \beta_0 + \sum_{i=1}^{n} \beta_i \, \Delta X_{it} + \varepsilon_t$$

Both Andrén et al. (2005) and Yan et al. (2014) argues that the relative importance of these macroeconomic and market exposures is indicated by the goodness of fit statistic (R^2). In this thesis, the relative importance is given by various coefficients while R^2 portray the (final risk exposure) model's goodness of fit statistic. As an essential part of a CFaR-calculation, the coefficients (β) produced by such a regression provide measures of the firm's risk exposure. These coefficients could then be used to determine the size of a firms positions in their attempt to mitigate the risk exposures movements.

After modelling a company's risk exposures based on the MUST (Macroeconomic Uncertainty Strategy) framework (Oxelheim & Wihlborg, 1987, 1997, 2005), one can then calculate the CFaR through simulations. Since the model resembles a company's different exposures, the information gained can be used to predict how a hedging contract or change in financial structure will affect the risk profile. Given that the model comprises of various macroeconomic- and market risks, which can be attributed a certain amount of the cash flow variability, the method of Andrén et al. (2005) provides information about the remaining part necessary to calculate the firm's overall variability in CFaR (Andrén et al., 2005).

All variables (except the German electricity price) included in the regressed model, are included in the model of Andrén et al. (2005). This is done in order to control for the different risk exposures, and, to be in accordance with economic theory (Yan et al., 2014).

5.4 Simulation of cash flow-at-risk:

The purpose of the simulation is to derive distributions of cash flow conditioned on significant market and macroeconomic risk exposures. Given that aluminium is the main commodity of Norsk Hydro ASA, the following simulation unfolds to changes in the price of aluminium. Employing the *normal inverse* and *randomized* functions of Microsoft Excel, expected values of EBITDA and Palu (i.e. mean) and standard deviations of the initial gathered data, in addition to correlations and beta-coefficients of the regressed risk exposures (i.e. the risk exposures respective periodic changes) plus their range of initial observations (relative to the range of the aluminium price – i.e. range ratio); a distribution of EBITDA is derived, conditioned on significant risk exposures. The simulation is based on a few simplified simplifying assumptions:

(1) Expected quarterly cash flow is assumed to correspond with mean price of the main commodity.
(2) Simulated values below or above the mean price are assumed to be number of units change in the main commodity, which then are met with changes in the other risk exposures conditioned on their correlation, range ratio and beta-coefficients.
(3) The natural range of possible units differs significantly from one exposure to another, making it necessary to scale the number of units with respect to each other.

The iterations of the market risk exposures are based on the correlation matrix, i.e. changes in one market risk exposure are "met" with a corresponding change in significantly correlated market risk exposures. Based on these simplified assumptions, it should be possible to estimate cumulated EBITDA with respect to each variable's respective beta-coefficient.

In each and every iteration, randomly-picked values are inserted into the regression model, generating a simulated value of cash flow conditional on market (and macroeconomic) variables. 10 000 scenarios were simulated, generating 10 000 simulated values of cash flow.

To estimate CFaR and total cash flow, it is necessary to complement the cash flow distribution, conditional on market risk exposures, with a distribution of macroeconomic risk exposures in addition to an error term. If the error term is well behaved, one can simply draw a value from a normal distribution ($\varepsilon \sim N(0,\sigma 2)$) and add that value to the conditional distribution. As described in chapter 5.1, the EB CFaR-calculation is a six-step process, for which (1) the chosen data set (CF_t, X_t) is from 2007 to 2016; (2) calculation the mean and correlation matrix for the first differences (ΔX_{it}); (3) generating 10 000 new ΔX_{2017Q1} based on the mean and correlation matrix:

$$\Delta X_{2017Q1} \sim N(\mu, \Omega)$$

Where the mean vector: $\mathrm{\mu} = \mathrm{E}(\Delta X_{1,2017}, \Delta X_{2,2017} \dots \Delta X_{n,2017})$ and the correlation vector: $\Omega = \mathrm{CORR}(\Delta X_{i2017}, \Delta X_{j2017})_{i,j=1,2\dots n}$.. and then (4) generating 10 000 new error terms (ε_{2017Q1}):

$$\varepsilon_{2017Q1} \sim N(0, \sigma^2)$$

(5), predicting the cash flow of Hydro Group in 2017 as a sum of the intercepts, the simulated variables multiplied by exposure coefficients, and error terms:

$$\Delta CF_{2017Q1}^{DC} = \beta_0 + \sum_{i=1}^{n} \beta_i \, \Delta X_{i,2017Q1} + \varepsilon_{2017Q1}$$

Then finally, (6) deriving the distribution of quarterly cash flow in 2017Q1:

$$CF_{2017Q1} = E(CF_{2017Q1}) + \Delta CF_{2017Q1}$$

Selecting a 95 percent confidence level, the average 5th percentile cash flow makes up for the limit with respect to a Cash Flow at Risk estimation.

5.5 Assumptions of regression

The eight assumptions of regression (see Berry, 1993, p. 12) are there to make sure that the estimated coefficients of the exposure model are substantiated in statistical prerequisites. Andrén et al. (2005) emphasises the statistical properties of the finalized exposure model, of which these 8 assumptions describe to a certain extent. Assessments of each assumption are presented in appendix 1. These assumptions are (Berry, 1993, p. 12):

A1.	All *independent* variables (X_1, X_2, . . . , X_k) are quantitative or dichotomous and the dependent variable, Y is quantitative, continuous, and unbounded. Moreover, all variables are measured without error.
A2.	All independent variables have *nonzero* variance (i.e. each independent variable has some variation in value).
A3.	There is not *perfect multicollinearity* (i.e. there is no exact linear relationship between two or more independent variables).
A4.	At each set of values for the k independent variables, (X_{1j}, X_{2j}, . . . , X_{kj}), $E(\varepsilon_j \mid X_{1j}, X_{2j}, \ldots, X_{kj}) = 0$ (i.e., the mean value of the error term is zero).
A5.	For each X_i, $COV(X_{ij}, \varepsilon_j) = 0$ (i.e., each independent variable is uncorrelated with the error term).
A6.	At each set of values for the independent variables, (X_{1j}, X_{2j}, . . . , X_{kj}), $VAR(\varepsilon_j \mid X_{1j}, X_{2j}, \ldots, X_{kj}) = \sigma^2$, where σ^2 is a constant (i.e., the conditional variance of the error term is constant); this is known as the assumption of homoscedasticity.
A7.	For any two observations, (X_{1j}, X_{2j}, . . . , X_{kj}) and (X_{1h}, X_{2h}, . . . , X_{kh}), $COV(\varepsilon_j, \varepsilon_h) = 0$ (i.e., error terms for different observations are uncorrelated; this assumption is known as a lack of autocorrelation.
A8.	At each set of values for the k independent variables, ε_j is normally distributed.

6 Results

The aim of this thesis was to apply the Exposure-Based Cash Flow at Risk approach to the most cash flow-sensitive divisions of Norsk Hydro ASA, i.e. the sale of primary aluminium, casting, extrusion and rolling. The simulation relies on both the correlations and the results of the regressed risk exposures; governing the order in which they are presented.

Following Andrén et al. (2005) and Yan et al. (2014), deriving a statistically strong risk exposure model requires high statistical significance, a high goodness of fit (R^2), no serial correlation and well-behaved error terms.

6.1 Exposure-Based model

The correlations of the risk variables determine their movements with respect to each other, Table 2 presents these correlations. These correlations are essential in order to get a realistic distribution of EBITDA, i.e. they partly determine the manifestation of movements in cash flow. In addition, the mean and standard deviation of each variable are presented in order to get a comprehension of the expected values and their average deviations; which are also relevant regarding the simulation.

The line in Table 2 separates the correlations, with the final risk exposures to the left. The most significantly correlated risk variable come out of the first row, i.e. those between the price of aluminium (P_{alu}) and $S_{nok/€}$, π_{nor} and π_{euro}, respectively. The correlation matrix describes each variable's relationship with respect to the periodic changes (i.e. the change from one period to the next period). The correlation between Palu and π_{euro} is relatively high, at 0,651 (significant at the 0,01 level), but should not imply a problem of multicollinearity.

Table 2: Means and Standard deviations, and correlations.

	Mean	2036	8,310	2,096	1,481	574	46,22	6,422	2,183	2,99	2,769	1,77
	Std.Dev	P_{alu}	$S_{NOK/€}$	π_{nor}	π_{euro}	PAS	P_{el}	$S_{nok/\$}$	i_{ger}	i_{nor}	$i_{u.s.}$	$\pi_{u.s.}$
P_{alu}	426,74	1	-,457**	,302	,651**	,522**	,604**	-,467**	,440**	,376	,457**	,643**
$S_{NOK/€}$	0,6467		1	,045	-,379*	-,111	-,085	,624**	-,112	-,114	-,073	-,426**
π_{nor}	1,0830			1	,268	,189	,389*	-,017	-,035	,056	,102	,120
π_{euro}	1,2149				1	,292	,585**	-,292	,317*	,141	,170	,817**
PAS	86					1	,399*	-,226	,220	,206	,268	,245
P_{el}	13,09						1	-,057	,391*	,369*	,403*	,439**
$S_{nok/\$}$	1,05							1	-,279	-,288	-,118	-,369*
i_{ger}	1,39								1	,870**	,821**	,512**
i_{nor}	1,17									1	,875**	,296
$i_{u.s.}$	,906										1	,290
$\pi_{u.s.}$	1,49											1

***sig. at the 0,01 level, *sig. at the 0,05 level. The means and standard deviations are those of each variables levels, while the correlations are those of periodic changes.*

Andrén et al. (2005) and Oxelheim and Wihlborg (1997) argue that a final exposure model consists of up to 5 variables, with adequate statistical properties. Before the selection of these variables can take place, the results of all variables have to be analysed. Table 3 show the result for the linear regression estimation of all the proposed risk exposures, showing a tendency of high VIF-values (Variance Inflation Factor) among the 10 Year Bonds, of which Δi_{nor} (8,336), Δi_{ger} (7,628) and $\Delta i_{u.s.}$ (6,794) show values above the limit of 5 (i.e. the limit regarding samples < 200) (Wenstøp, 2006). Significant variables consist of ΔP_{alu} (,013), $\Delta S_{NOK/€}$ (,003), $\Delta\pi_{nor}$ (,018), $\Delta\pi_{euro}$ (,009), ΔPAS (,020) Δi_{nor} (,017) and $\Delta i_{u.s.}$ (,001).

Table 3: Risk exposure model - all variables included

	UnStdzd.		Stdzd.			
	Beta	Std. error	Beta	Sig.	tolerance	VIF
Intercept	1,368	93,349		,988		
ΔP_{alu}	1,946	,729	,425	,013	,253	3,954
$\Delta S_{NOK/€}$	-1084,662	326,643	-,388	,003	,469	2,133
$\Delta\pi_{nor}$	332,404	131,698	,240	,018	,707	1,415
$\Delta\pi_{euro}$	-905,240	319,495	-,481	,009	,222	4,497
ΔPAS	5,519	2,235	,240	,020	,679	1,473
ΔP_{el}	32,342	27,039	,152	,242	,398	2,513
$\Delta S_{nok/\$}$	-126,948	318,980	-,051	,694	,391	2,560
Δi_{nor}	-2005,418	785,311	-,590	,017	,120	8,336
Δi_{ger}	-121,585	729,170	-,037	,869	,131	7,628
$\Delta i_{u.s.}$	2072,283	568,841	,760	,001	,147	6,794
$\Delta\pi_{u.s.}$	-94,468	156,209	-,105	,550	,212	4,719
R^2	0,827					
Adjusted R^2	0,757					
Durbin-Watson	2,216					
Std. error	527,352					
N	39					

Compared to the results of Andrén et al. (2005), the most noticeable are the exposures to the exchange rates of NOK/USD (-126,948 with a significance of ,649) and NOK/EURO (-1084,662 with a significance of ,003), which Andrén et al. (2005) found to be -392 (sig.=,09) and 702 (sig.=0,06) respectively.

Whether the lack of significance exposures to the NOK/USD exchange rate was due to Hydro's adequate hedging of their NOK/USD-exposure, or due to the "*foreign exchange exposure puzzle*" is hard to say (Hutson & Laing, 2014, p. 98). One reason might be that "*Hydro's downstream business is based in Europe and a large portion of the production is sold in Euro while export sales to other regions are typically denominated in US dollars*" (Hydro, 2016, p. 26). If the risk exposure of sale denominated in US dollars is too small to be detected empirically, then the risk exposure to NOK/USD exchange rate might not be of importance with respect to the downstream divisions cash flow. Another reason might be that "*Hydro's primary foreign currency risk is linked to fluctuations in the value of the US dollar versus the currencies in which significant costs are incurred*" (Hydro, 2016, p. F32). This implies that the relative costs of production might not be captured by the exchange rate, but by the inflation in Europe and Norway.

The following exposure model comes as a result of omitting variables in Table 3 that show high VIF-values and then low significance. The finalized risk exposure model consists of 4 significant risk exposures , which seems to be within the expected range of Andrén et al. (2005) and Oxelheim and Wihlborg (1997). Table 4 show the result for the linear regression estimation of ΔP_{alu}, $\Delta S_{nok/euro}$, $\Delta\pi_{nor}$ and $\Delta\pi_{euro}$ in addition to ΔPAS (Primary Aluminium Sold in metric tonnes). They are all significant (0,000, 0,011, 0,011, 0,000 and 0,022, respectively), sum up to a high statistical goodness of fit (Adj R^2 = 0,661) and the Durbin Watson coefficient (2,210) implies a negligible negative serial correlation. The error term is, in general, well behaved but have some minor tendencies of bad behaviour (see appendix 1 for further assessments). Both the European and Norwegian inflation are important macroeconomic risk exposures, as cash flow of Norsk Hydro ASA's processing divisions are influenced by fluctuations in the price level of both areas (standardized betas were -,577 and ,277 respectively). In addition, the (US Dollar denominated) aluminium price and exchange rate of Norwegian Krone to Euros show a significant portion of the explained variance (with a standardized beta of ,645 and -,299 respectively). Andrén et al. (2005) acknowledged the possible non-linear relationships in their study, but the simulations require linear coefficients. Further testing of the relationships between the independent risk exposures and the dependent variable showed significant curve-linear relationships for the included risk exposures, weakening the accuracy of the linearly significant relationships (see appendix 2 – 6).

Table 4: Risk exposure model – ΔP_{alu}, $\Delta S_{nok/euro}$, $\Delta\pi_{nor}$ and $\Delta\pi_{euro}$

	UnStdzd.		Stdzd.			
	Beta	Std. error	Beta	Sig.	tolerance	VIF
Intercept	28,150	101,880		,784		
ΔP_{alu}	2,954	,645	,645	,000	,387	2,583
$\Delta S_{NOK/€}$	-836,797	310,898	-,299	,011	,721	1,387
$\Delta\pi_{nor}$	383,379	141,576	,277	,011	,852	1,173
$\Delta\pi_{euro}$	-1049,959	238,490	-,557	,000	,556	1,798
ΔPAS	6,231	2,589	,271	,022	,705	1,418
R^2	0,706					
Adjusted R^2	0,661					
Durbin-Watson	2,210					
Std. error	622,567					
N	39					

Using the unstandardized beta-coefficients, the simulation of cash flow comes as a result of both the regressed sensitivities and correlation coefficients. Simulations based on various compositions of variables is the benefit of EB CFaR, i.e. one can always change the composition in order to see the derived distribution of cash flow; in addition to the possibility of alternating between time periods.

The surprising result is that of Hydro's exposure to the NOK/EURO exchange rate, which Andrén et al. (2005) found to be a 702 million increase per unit NOK/EURO depreciation, seems to be negative. Hydro does, however, have a different operational position today than back in the days of Andrén et al. (2005) study; e.g. with their large investments in German production of aluminium products (source) (Hydro, 2018d). An interesting question is to what extent the Premium added to the aluminium price would account for the exposure; i.e. if the aluminium price is purely a price for the metric tonnes of aluminium bought, a closer look at the drivers of the premium could reveal some measures of possible hedging strategies.

EB CFaR opens up rich possibilities for decomposing the final CFaR estimate into one or a group of related risk exposures. Andrén et al. (2005) argues that this provides insight into the cash flow dynamics of the company and the respective key drivers of risk. As the results of the simulation will show, it is always possible to compare compositions of exposures in the attempt to see what kind of effect the inclusion of one, or groups of, risk exposure(s) entail.

6.2 Exposure-Based Cash Flow at Risk estimation

Table 5 presents the expected cash flow and CFaR. The first (second) row presents the results when the market variables of ΔP_{alu} and $\Delta S_{nok/euro}$ (ΔP_{alu} and $\Delta S_{nok/€}$, $\Delta\pi_{nor}$, $\Delta\pi_{euro}$) are used. The expected Cash Flow of Norsk Hydro ASA's downstream business, which is the average cash flow, is shown in column (A); cash flow at the 5th percentile is presented in column (B); Cash flow at Risk, which is the difference between expected cash flow and cash flow at the 5th percentile, is reported in Column (C), and the cash flow in percentage, which is cash flow at risk divided by the expected cash flow is reported in column (D). A noticeable difference between the first and second row is that the inclusion of $\Delta\pi_{nor}$ and $\Delta\pi_{euro}$ reduces the percentage CFaR from 147,8 % to 84,3 percent.

Table 5: Exposure-Based CFaR quarterly-estimates.

Cash flow conditioned on	Expected Cash Flow (A)	5th percentile Cash Flow (B)	CFaR (C = A-B)	CFaR in percent (D = C /A)
ΔP_{alu} and $\Delta S_{nok/euro}$	1672	-800	2472	147,8 %
ΔP_{alu} and $\Delta S_{nok/€}$, $\Delta \pi_{nor}$, $\Delta \pi_{euro}$	1672	262	1410	84,3 %

The distribution of cash flow conditioned on the price of aluminium (ΔP_{alu}) and exchange rate of NOK/EURO ($\Delta S_{nok/euro}$) are shown in Figure 2, and the distribution conditioned on market and macroeconomic exposures shown (ΔP_{alu} and $\Delta S_{nok/€}$, $\Delta \pi_{nor}$, $\Delta \pi_{euro}$) in Figure 3. The results of Table 5 and Figure 2 and 3 show a significant difference in the distribution of cash flow and CFaR. For instance, the percentage of CFaR (column D) indicates a noticeable difference when the European and Norwegian inflation are included in the simulation. The frequency of the distributions (see Figure 2 – 4) indicates the amount of simulated cash flows; with lower scales indicating a wider range of simulated cash flows – given the constant number of simulations of 10 000).

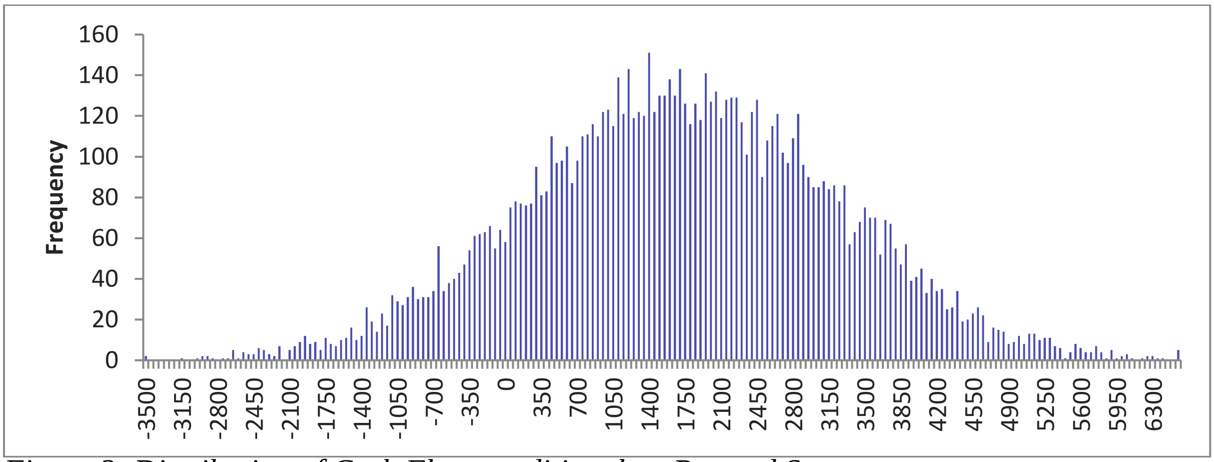


Figure 2: Distribution of Cash Flow conditional on P_{alu} and $S_{nok/euro}$

The robustness of the simulation of Cash Flow for the downstream business rests on the statistical properties of the exposure model. Assuming the estimation of the risk exposures are accurate, the two CFaR-calculations reveal a large macroeconomic influence in that the calculated CFaR conditioned on P_{alu} and $S_{nok/euro}$ (CFaR=2472) differs significantly from the CFaR conditioned on both market and macroeconomic variables (CFaR=1410). This can be attibruted to the negative beta-coefficient of the European inflation (-1049,959) in combination with the positive correlation with the aluminium price (0,651), makes up for a risk dampening effect. The distributions of figure 2 and 3 give some insight into the influence of the European inflation, and that it dampens the influence of fluctuations in the price of aluminium and NOK/EURO exchange rate, on cash flow. The placement of a Cash flow of 0 (in the figures of distribution) implies the probability of large losses – with lower risk of large deficits associated with a placement of 0 further to the left.

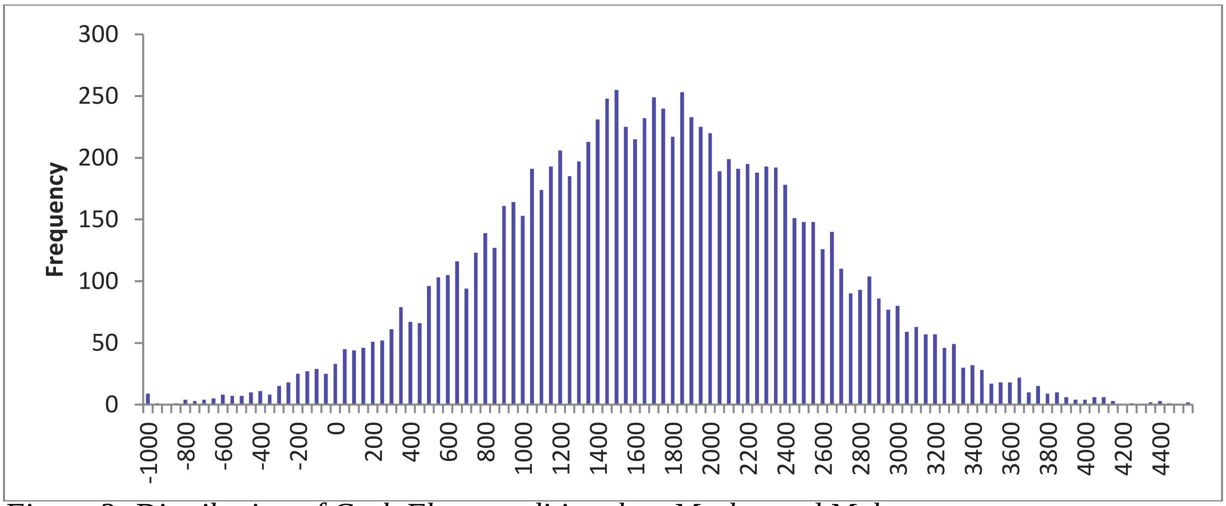


Figure 3: Distribution of Cash Flow conditional on Market and Makro exposures

6.3 Normal market conditions – Cash Flow at Risk

If the years of high risk (2007-2009) are excluded from the estimations of – the regressed risk exposures and the expected values of the various risk exposures – the remaining observations could result in what to expect under normal market conditions. The following results are for comparison to the results of all observations and provide some insight into the expected cash flow if there is no rare event such as a financial crisis.

On the basis that aluminium is Norsk Hydro ASA's main commodity and the distribution of the aluminium price affect the distribution of simulated cash flow (see section 5.3), a reduction in the standard deviation of P_{alu} could the distribution of simulated quarterly cash flow. For instance, the mean of the aluminium price from 2010 to 2016 is 1924 with a standard deviation of 289,8 (compared to a mean of 2036 and a std.dev of 426,74 in 2007 to 2016). In addition, the mean of observed EBITDA-numbers is 1662 (compared to 1672 as the mean of 2007-2016) with a standard deviation of 636,16 (1244 of 2007-2016). As before, simulations are dependent on correlations and a finalized exposure model – compliant with the statistical properties emphasised by Andrén et al. (2005). Table 6 presents the correlations of periodic changes in the period of 2010 throughout 2016.

Table 6: Correlation of periodic changes under normal market conditions.

	P_{alu}	$S_{nok/\$}$	$S_{NOK/€}$	π_{euro}	PAS	P_{el}	i_{nor}	π_{nor}	i_{ger}	$i_{u.s.}$	$\pi_{u.s.}$
P_{alu}	1	-,357	-,288	,399*	,173	,480*	, 282	,138	,339	,303	,518**
$S_{nok/\$}$		1	,512**	-,181	-,213	-,005	-,163	-,106	-,105	,057	-,375
$S_{NOK/€}$			1	-,307	-,097	-,026	,146	-,096	,200	,200	-,087
π_{euro}				1	-,085	,543**	-,008	-,229	,128	,074	,663**
PAS					1	,240	,190	-,078	,202	,120	,239
P_{el}						1	,220	-,264	,331	,317	,523**
i_{nor}							1	,127	,898**	,909**	,238
π_{nor}								1	,032	,164	-,048
i_{ger}									1	,911**	,308
$i_{u.s.}$										1	,248
$\pi_{u.s.}$											1

Table 7 show the result for the linear regression estimation of all the proposed risk exposures, showing a tendency of high VIF-values (Variance Inflation Factor) among the 10 Year Bonds, of which Δi_{nor} (10,149), Δi_{ger} (9,919) and $\Delta i_{u.s.}$ (15,063) show values above the limit of 5 (i.e. the limit regarding samples < 200) (Wenstøp, 2006). In order to get a statistically adequate risk exposure model, variables are omitted by their high VIF-values, then by statistical significance.

Table 7: Risk exposure model - all variables - normal conditions

	UnStdzd.		Stdzd.			
	Beta	Std. error	Beta	Sig.	tolerance	VIF
Intercept	-107,939	94,571		,273		
ΔP_{alu}	2,486	,612	,612	,004	,516	1,936
$\Delta S_{NOK/€}$	-629,582	410,454	-,301	,147	,423	2,362
$\Delta \pi_{nor}$	-50,688	181,190	-,044	,784	,658	1,519
$\Delta \pi_{euro}$	-1015,753	414,581	-,569	,028	,275	4,497
ΔPAS	4,154	2,215	,295	,082	,661	1,473
ΔP_{el}	-28,644	41,293	-,133	,499	,444	2,252
$\Delta S_{nok/\$}$	132,728	333,911	,088	,697	,331	3,018
Δi_{nor}	-1339,499	750,473	-,726	,096	,099	10,149
Δi_{ger}	-1019,55	729,170	-,519	,218	,101	9,919
$\Delta i_{u.s.}$	2153,887	568,841	1,304	,020	,066	15,063
$\Delta \pi_{u.s.}$	-94,468	156,209	,068	,776	,293	3,413
R^2	0,772					
Adjusted R^2	0,592					
Durbin-Watson	2,173					
Std. error	375,296					
N	28					

Table 8 show the results of the finalized risk exposure model under normal market conditions. One of the results that differ from the model under high risk period (2007-2016) (see Table 3 and 4) is the exposure to the NOK/USD exchange rate with a UnStdzd. Beta of 549,803 and sig. of ,038 (see Table 8); the remaining risk exposures are all significant except the control variable of ΔPAS. With an Adjusted R2 of ,545 and a Durbin Watson coefficient of 2,295, the model seems to be founded in the emphasised statistical properties of Andrén et al. (2005), i.e. a high statistical goodness of fit, significant variables and no serial correlation of concern; although the Durbin-Watson coefficient indicates a negative serial correlation.

Table 8: Risk exposure model - Finalized - normal conditions

	UnStdzd.		Stdzd.			
	Beta	Std. error	Beta	Sig.	tolerance	VIF
Intercept	1,945	79,79		,784		
ΔP_{alu}	2,725	,639	,671	,000	,735	1,36
$\Delta S_{nok/\$}$	549,803	247,908	,365	,038	,671	1,49
$\Delta S_{NOK/€}$	-778,696	340,039	-,372	,033	,689	1,452
$\Delta \pi_{euro}$	-981,441	261,541	-,576	,001	,772	1,2958
ΔPAS	3,384	1,991	,240	,105	,913	1,095
R^2	0,636					
Adjusted R^2	0,545					
Durbin-Watson	2,295					
Std. error	396,563					
N	28					

In contrast to the results including high risk periods, ΔPAS does not seem to have a statistically significant influence (,105), which could imply that the quarterly sold quantum of aluminium is to stable to function as a control variable under normal market conditions.

Table 9 presents the expected cash flow and CFaR conditioned on normal market conditions, and the variables of ΔP_{alu}, $\Delta S_{nok/\$}$, $\Delta S_{NOK/€}$, and $\Delta\pi_{euro}$. The expected Cash Flow of Norsk Hydro ASA's downstream business, which is the average cash flow, is shown in column (A); cash flow at the 5th percentile is presented in column (B); Cash flow at Risk, which is the difference between expected cash flow and cash flow at the 5th percentile, is reported in Column (C), and the cash flow in percentage, which is cash flow at risk divided by the expected cash flow is reported in column (D). Table 9 show a 5th percentage cash flow of 310, which gives a CFaR estimate of 1352 with a CFaR-percentage of 81,3 %; compared to the CFaR-percentage of the included high-risk period (84,3 % - Table 5), this is a small decrease in CFaR (%).

Table 9: CFaR-estimation under normal market conditions

Cash flow conditioned on	Expected Cash Flow (A)	5th percentile Cash Flow (B)	CFaR (C = A-B)	CFaR in percent (D = C /A)
ΔP_{alu}, $\Delta S_{nok/\$}$, $\Delta S_{NOK/€}$, $\Delta\pi_{euro}$	1662	310	1352	81,3 %

The high volatility of quarterly earnings in the 2007 – 2009 period lead to a higher average cash flow than the following 2010 – 2016 period. The lower volatility of the aluminium price implies that the earnings should be more stable, as the percentage CFaR of 81,3 % (compared to 84,3 % in Table 4) would indicate. Figure 4 show the distribution of quarterly earnings under normal market conditions, conditioned on ΔP_{alu}, $\Delta S_{nok/\$}$, $\Delta S_{NOK/€}$, and $\Delta\pi_{euro}$, and there seems to be a higher frequency of estimated earnings around the mean (1662).

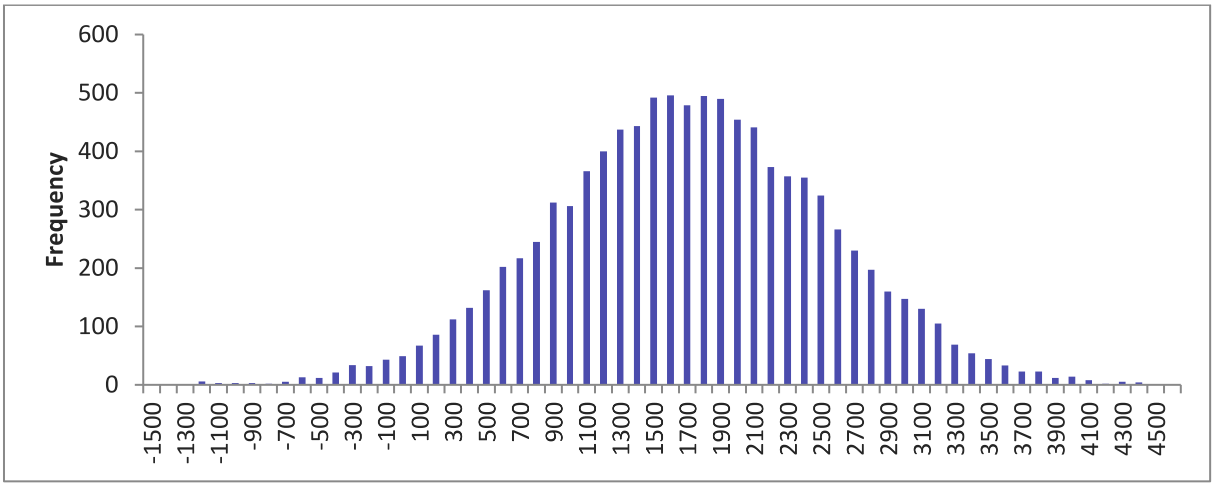


Figure 4: Distribution of Cash Flow conditioned on P_{alu}, $S_{nok/euro}$, $S_{nok/euro}$ and π_{euro} - Normal market conditions.

7 Conclusion

The application of the Exposures-Based Cash Flow-at-Risk framework is a applicable model that effectively portray risk associated with cash flow. Even though the process of it is somewhat complicated, and require a fundamental understanding of both economic theory, simulation and statistics, the end result is simple yet influential in terms of understanding the risk exposure scenery. In high risk periods the earnings of Norsk Hydro ASA's downstream divisions seem to be stabilized by the positive correlation of the aluminium price and European inflation in addition to the negative exposure to the European Inflation.

As Andrén et al. (2005) argued, the EB CFaR framework and the following simulations opens up rich possibilities in terms of different circumstantial conditions. The results of normal market conditions indicate that there is a 5 percent probability of earnings of 310 million NOK, with a significantly higher frequency of simulated earnings around the expected amount.

For further research, there are several questions that could be pursued in the attempt to advance our understanding of the Exposures Based Cash Flow-at-Risk model. For instance, number of firms and industries this framework could be applied to are many, which begs the question whether this framework would stand the test of further application. The question whether or not measures of risk exposures have a real-world significance and to the degree that these actually measure inputs the case firm deal with, is a big one in estimating or putting together a valid risk exposure model. Oxelheim and Wihlborg (1997) argued that the task of comprehending the multifaceted sceneries of risk is difficult but should not be avoided; making the attempt a step forward out of many.

At last, Andrén et al. (2005) mentions curve-linear relationships among variables, which is present in the appended curve estimation (2-6) and could be pursued to search for models with higher statistical goodness of fit.

References/bibliography

Andrén, N., Jankensgård, H., & Oxelheim, L. (2005). Exposure-Based Cash-Flow-at-Risk: An Alternative to VaR for Industrial Companies. *Journal of Applied Corporate Finance, 17*(3), 76-86.

Bartram, S. M., & Bodnar, G. M. (2007). The exchange rate exposure puzzle. *Managerial Finance, 33*(9), 642-666. doi:10.1108/03074350710776226

Berry, W. D. (1993). *Understanding regression assumptions* (Vol. 92): Sage Publications.

Bodie, Z. (1983). Commodity futures as a hedge against inflation. *The Journal of Portfolio Management, 9*(3), 12-17.

Bodie, Z., & Rosansky, V. I. (1980). Risk and return in commodity futures. *Financial Analysts Journal, 36*(3), 27-39.

Bodnar, G. M., Hayt, G. S., & Marston, R. C. (1996). 1995 Wharton survey of derivatives usage by US non-financial firms. *Financial management*, 113-133.

Bodnar, G. M., Hayt, G. S., & Marston, R. C. (1998). 1998 Wharton survey of financial risk management by US non-financial firms. *Financial management*, 70-91.

Bodnar, G. M., Hayt, G. S., Marston, R. C., & Smithson, C. W. (1995). Wharton survey of derivatives usage by US non-financial firms. *Financial management, 24*(2), 104-114.

Bollen, N. P. B., & Whaley, R. E. (2009). Hedge Fund Risk Dynamics: Implications for Performance Appraisal. *Journal of Finance, 64*(2), 985-1035. doi:10.1111/j.1540-6261.2009.01455.x

Casassus, J., Liu, P., & Tang, K. (2012). Economic linkages, relative scarcity, and commodity futures returns. *The Review of Financial Studies, 26*(5), 1324-1362.

Chng, M. T. (2009). Economic linkages across commodity futures: Hedging and trading implications. *Journal of Banking & Finance, 33*(5), 958-970.

Chuang, C.-C., Wang, Y.-H., Yeh, T.-J., & Chuang, S.-L. (2015). Hedging effectiveness of the hedged portfolio: the expected utility maximization subject to the value-at-risk approach. *Applied Economics, 47*(20), 2040-2052.

Cotter, J., & Hanly, J. (2012). Hedging effectiveness under conditions of asymmetry. *The European Journal of Finance, 18*(2), 135-147.

Dutta, A., & Hasib Noor, M. (2017). Oil and non-energy commodity markets: An empirical analysis of volatility spillovers and hedging effectiveness. *Cogent Economics & Finance, 5*(1), 1324555.

Elaine, H., & Simon, S. (2009). Openness, hedging incentives and foreign exchange exposure: A firm-level multi-country study. *Journal of International Business Studies, 41*(1), 105. doi:10.1057/jibs.2009.32

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1993). Risk management: Coordinating corporate investment and financing policies. *The Journal of Finance, 48*(5), 1629-1658.

Haigh, M. S., & Holt, M. T. (2002). Hedging foreign currency, freight, and commodity futures portfolios—A note. *Journal of Futures Markets, 22*(12), 1205-1221. doi:10.1002/fut.10050

Hillier, D., Grinblatt, M., & Titman, S. (2012). *Financial Markets and Corporate Strategy (second European ed.)*.

Huldeborg, E. H. (2013). *The weekend volatility effect, Value at Risk and option pricing in the market for gold futures at the Chicago mercantile exchange.* Norwegian University of life sciences,

Hutson, E., & Laing, E. (2014). Foreign exchange exposure and multinationality. *Journal of Banking & Finance, 43*, 97-113.
Hydro. (2016). (1/2016). Retrieved from https://www.hydro.com/globalassets/1-english/investor-relations/annual-report/2016/downloads/annual-report-2016.pdf.
Hydro. (2018a). *Our History.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/
Hydro. (2018b). *Hydro + ÅSV = A strong Alloy.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/1978---19902/1986-Hydro--ASV--a-strong-alloy/
Hydro. (2018c). *Familiar throughout the world.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/1991---2005/2003-Familiar-throughout-the-world/
Hydro. (2018d). *VAW - a dream comes true.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/1991---2005/2002-VAW--a-dream-comes-true/
Hydro. (2018e). *Just aluminium 105 years on.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/2006--/Just-aluminium-105-years-on/
Hydro. (2018f). *2006 -.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/2006--/
Hydro. (2018g). *Hydro came full circle in Brazil.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/2006--/2011-Hydro-came-full-circle-in-Brazil/
Hydro. (2018h). *The worlds biggest manufacturer of aluminium extrusions.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/2006--/2013-The-worlds-biggest-manufacturer-of-aluminum-extrusions/
Hydro. (2018i). *100 % Aluminum.* Retrieved from https://www.hydro.com/en/about-hydro/Our-history/2006--/2011/
Hydro. (2018j). *Reports.* Retrieved from https://www.hydro.com/en/investor-relations/reports/
NorgesBank. (2018). *Valutakursjer - Månedlige gjennomsnitt.* Retrieved from https://www.norges-bank.no/Statistikk/Valutakurser/
Oxelheim, L., & Wihlborg, C. (1987). *Macroeconomic uncertainty-international risks and opportunities for the corporation*: John Wiley & Sons.
Oxelheim, L., & Wihlborg, C. (1997). Managing in the Turbulent World Economy. Corporate Performance and Risk Exposure.
Oxelheim, L., & Wihlborg, C. (2005). *Corporate performance and the exposure to macroeconomic fluctuations*: Nordstedts.
Quandl. (2018). *Aluminum Prices - London Metal Exchange.* Retrieved from https://www.quandl.com/data/LME/PR_AL-Aluminum-Prices
RiskMetrics. (1999). New York: RiskMetrics Group.
Stein, J. C., Usher, S. E., LaGattuta, D., & Youngen, J. (2001). A comparables approach to measuring cashflow-at-risk for non-financial firms. *Journal of Applied Corporate Finance, 13*(4), 100-109.
TradingEconomics. (2018). Retrieved from https://tradingeconomics.com/
Wenstøp, F. (2006). *Statistikk og dataanalyse* (9. utg. ed.). Oslo: Universitetsforl.

Yan, M., Hall, M. J., & Turner, P. (2014). Estimating Liquidity Risk Using The Exposure-Based Cash-Flow-At-Risk Approach: An Application To The Uk Banking Sector. *International Journal of Finance & Economics, 19*(3), 225-238.

Zhou, V. Y., & Wang, P. (2013). Managing foreign exchange risk with derivatives in UK non-financial firms. *International Review of Financial Analysis, 29*, 294-302.

Appendix

Appendix 1: specific assessment of each regression assumption

	Specifics of the exposure model.	Approved
A1.	All independent variables are quantitative or dichotomous and the dependent variable is quantitative, continuous and unbounded.	Yes
A2.	All variables have a variance ≠ *zero.* Only 2 (P_{alu}, P_{el}) variables has a variance larger than 100; 1 larger than 2 ($\pi_{U.S.}$); 5 between 1 and 2 ($S_{NOK/US}$, i_{nor}, π_{nor}, i_{ger}, π_{euro}); and then 2 with a variance less than 1 ($S_{NOK/EURO}$ and $i_{u.s.}$).	Yes
A3.	The correlation of each independent variable should be less than 0,6 (Wenstøp, 2006). The coefficients of the correlation matrix show that only the price of aluminium and the European Inflation measure have a correlation of above ,6 which is expected because of the significance of the German market. However, with a small sample of 40 observations, a VIF value of 5 would indicate problem multicollinearity (Wenstøp, 2006). With a P_{alu} VIF-value of 2,583, and the remaining variables between 1 and 2, the final exposure model does seem to be within a reasonable amount of multicollinearity.	Yes
A4.	Among the residual plots, there is a slight tendency to deviate from the line, but in general, all plots seem to follow the line without any severe signs of violation. There are some outliers of in the scatterplots, but they should not be of importance in further analysis. Regarding the curve estimation, and according to (Wenstøp, 2006), a difference > 0.02 of the estimated R^2 (quadratic/cubic implies that there might be a non-linear relationship between the independent and dependent variable, making the estimation of linear betas futile. Curve estimation shows a difference (Linear < quadratic) larger than 0,02 for all the remaining variables, but linear coefficients are necessary for the simulation, and hence, quadratic relationships are not analysed.	Yes
A5.	Violations of the 5th assumption comes in two ways. (1) Spurious effects which leads to overestimated beta-coefficients; or (2) masked effects to low coefficients or the wrong sign (i.e. + / -). Using Primary aluminium sold (metric tonnes) as a control variable, assessing the correlation matrix and respective coefficients showed that P_{alu} and π_{nor} had spurious effects while $S_{nok/euro}$ showed a masked effect. Including the control variable in the regression is done in order to lessen these effects.	Yes
A6.	The assumption of homoscedasticity is best examined by evaluating the independent variables specific scatterplots. All in all, the scatterplots of Palu and EuroInflation indicate that there is a violation of this assumption given the distribution of the residual.	Yes
A7.	The Durbin Watson is really only useful to function in testing is residuals are correlated serially from one observation to the next when you have a natural order. As the observations of both the dependent and independent variables are ordered in a chronologically manner, the assumption is of interest. The results of the Durbin-Watson test show that there is a significant serial correlation with a value of 2,121. Values of this test range between 0 and 4, with 2 as the neutral value, indicating no serial correlation, 0 as a perfectly positive and 4 as perfectly negative (Wenstøp, 2006).	Yes
A8.	The 8th is a two-step assumption test, for which (1) assessments of Skewness and Kurtosis and (2) looking for outliers are the two steps. Whereas Skewness concerns the (a-)symmetry of the distribution, Kurtosis concerns the pointiness. Ideally, both Skewness and Kurtosis should be 0, indicating a normal distribution. Positive values convey an (high value) asymmetric distribution and a pointy distribution. Whereas negative values, (low value) asymmetric distribution and flat, respectively (Sandvik, 2016). All in all, some values of Skewness and Kurtosis differs from 0, but the properties of the data do not give much room for good distributions. A case wise diagnostic test reveals no significant outliers outside of 3 standard deviations.	Yes

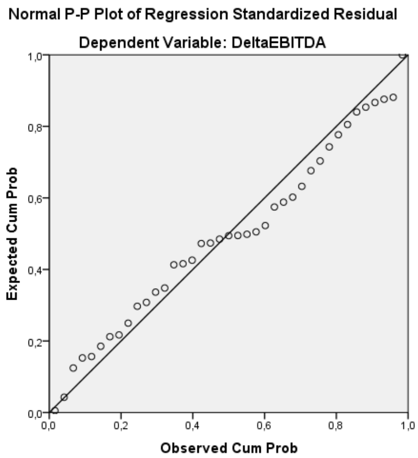
Appendix 2: Curve estimations and plots for Palu

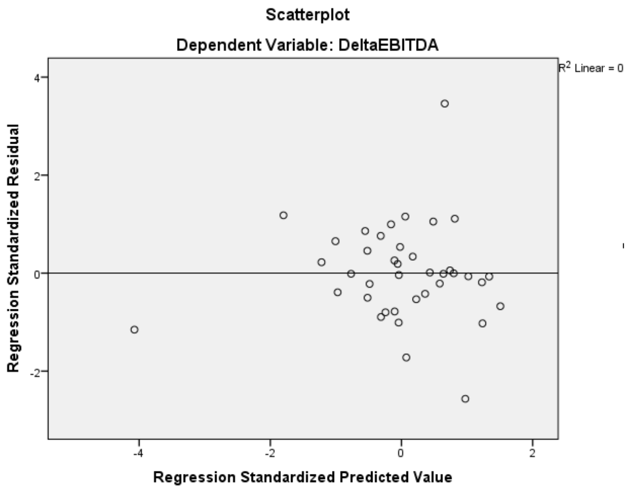
Model Summary and Parameter Estimates

Dependent Variable: DeltaEBITDA

Equation	Model Summary					Parameter Estimates		
	R Square	F	df1	df2	Sig.	Constant	b1	b2
Linear	,414	26,101	1	37	,000	13,124	2,947	
Quadratic	,446	14,495	2	36	,000	83,116	2,170	-,002

The independent variable is DeltaPalu.





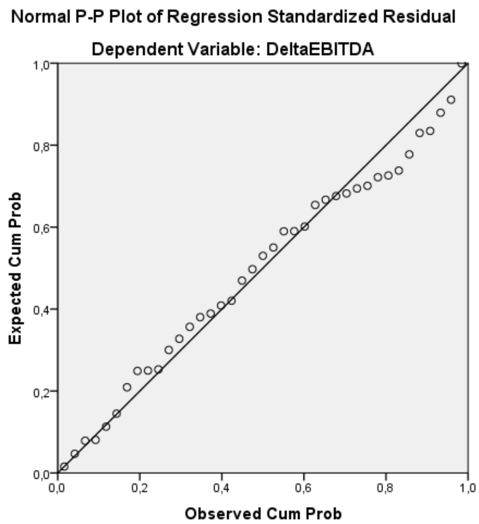
Appendix 3: Curve estimation and plots for NOK/EURO

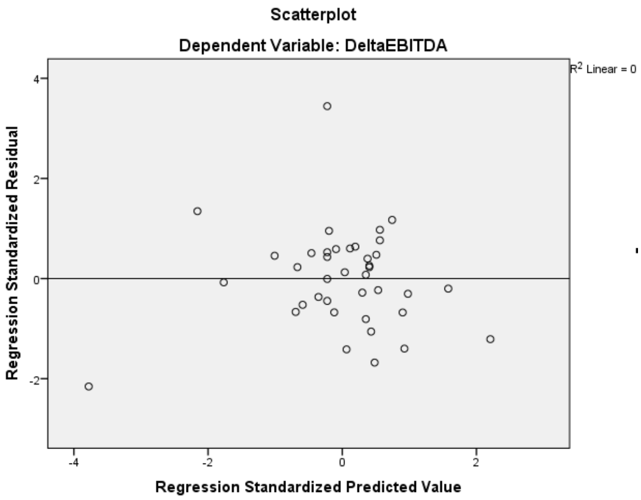
Model Summary and Parameter Estimates

Dependent Variable: DeltaEBITDA

Equation	Model Summary					Parameter Estimates		
	R Square	F	df1	df2	Sig.	Constant	b1	b2
Linear	,160	7,056	1	37	,012	-45,052	-1118,900	
Quadratic	,307	7,977	2	36	,001	131,341	-324,074	-1367,319

The independent variable is DeltaNok/EURO.





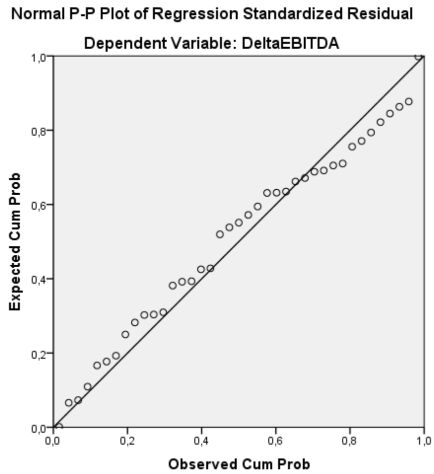
Appendix 4: Curve estimation and Plots for NorInfla.

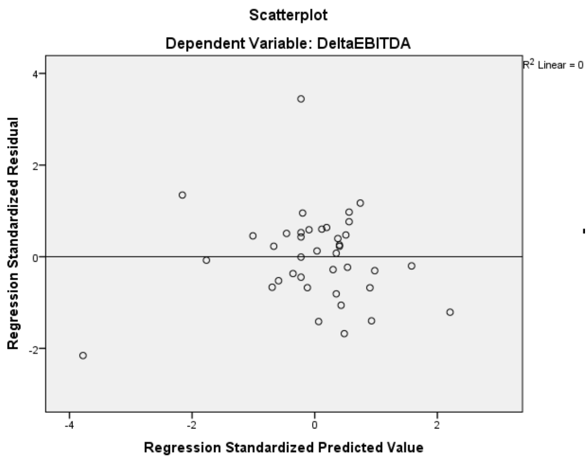
Model Summary and Parameter Estimates

Dependent Variable: DeltaEBITDA

Equation	Model Summary					Parameter Estimates		
	R Square	F	df1	df2	Sig.	Constant	b1	b2
Linear	,130	5,509	1	37	,024	-105,528	498,299	
Quadratic	,151	3,195	2	36	,053	,518	607,180	-193,289

The independent variable is DeltaNorInfla.





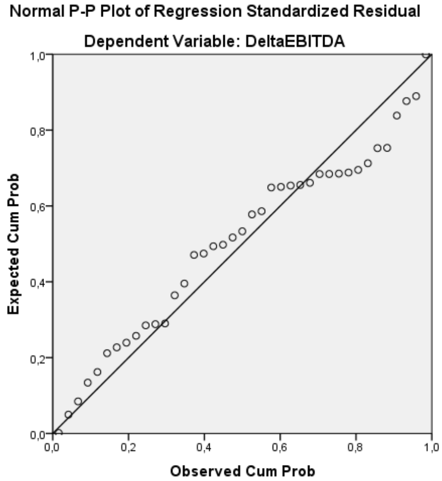
Appendix 5: Curve Estimation and Plots for EuroInfla

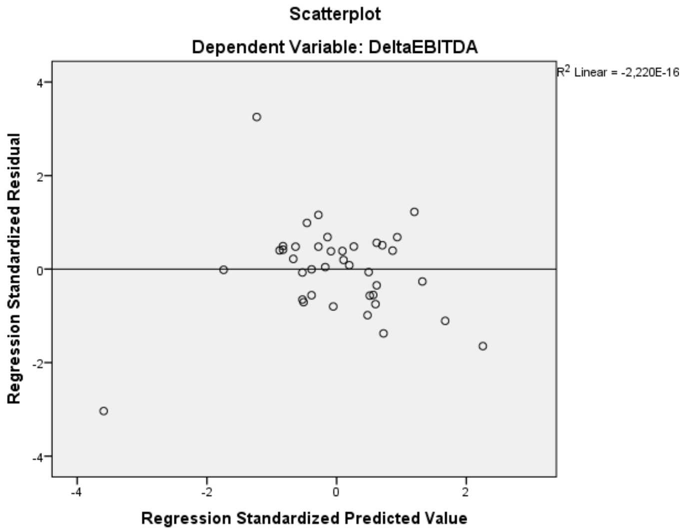
Model Summary and Parameter Estimates

Dependent Variable: DeltaEBITDA

Equation	Model Summary					Parameter Estimates		
	R Square	F	df1	df2	Sig.	Constant	b1	b2
Linear	,017	,627	1	37	,433	-67,318	243,244	
Quadratic	,341	9,322	2	36	,001	215,823	-253,739	-932,560

The independent variable is DeltaEuroInfla.





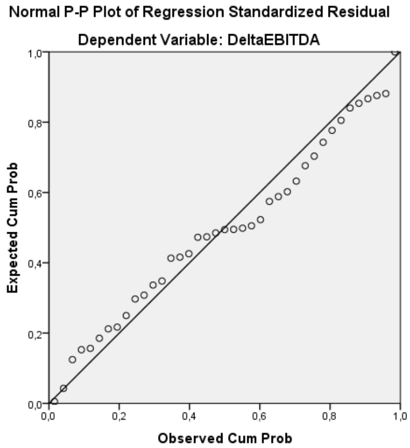
Appendix 6: Curve estimation and Plots for PrimAluSold

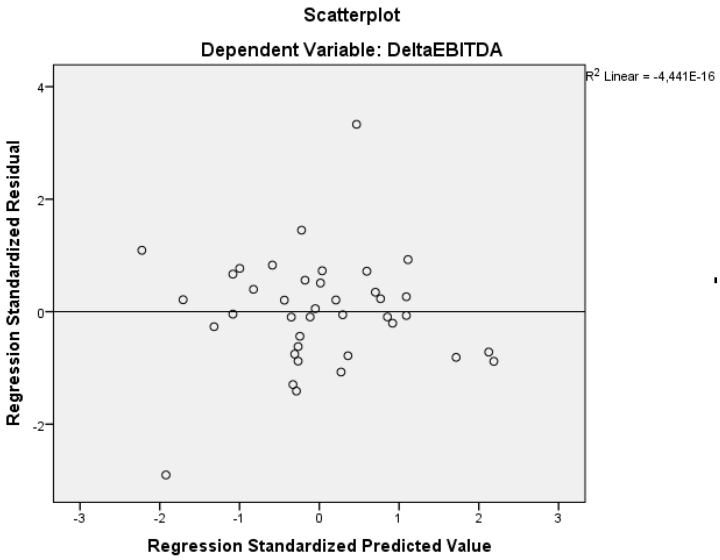
Model Summary and Parameter Estimates

Dependent Variable: DeltaEBITDA

	Model Summary					Parameter Estimates		
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2
Linear	,281	14,449	1	37	,001	9,035	12,201	
Quadratic	,313	8,182	2	36	,001	138,782	11,497	-,063

The independent variable is DeltaPrimAluSold metric tonnes.





Appendix 7: Correlations of risk exposures periodic changes.

Correlations

		DeltaEBITDA	DeltaPalu	DeltaPel	DeltaNok/USD	DeltaNok/EURO	Delta10yNGB	DeltaNorInfla	Delta10YGGB	DeltaEuroInfla	DeltaU.S.GB	DeltaU.S.Infla	DeltaPrimAlu Sold metric tonnes
DeltaEBITDA	Pearson Correlation	1	,643**	,380*	-,286	-,400*	,282	,360*	,216	,129	,479**	,141	,530**
	Sig. (2-tailed)		,000	,017	,078	,012	,082	,024	,187	,433	,002	,390	,001
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaPalu	Pearson Correlation	,643**	1	,604**	-,467**	-,457**	,376*	,302	,440**	,651**	,457**	,643**	,522**
	Sig. (2-tailed)	,000		,000	,003	,003	,018	,062	,005	,000	,003	,000	,001
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaPel	Pearson Correlation	,380*	,604**	1	-,057	-,085	,369*	,389*	,391*	,585**	,403*	,439**	,399*
	Sig. (2-tailed)	,017	,000		,731	,605	,021	,015	,014	,000	,011	,005	,012
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaNok/USD	Pearson Correlation	-,286	-,467**	-,057	1	,624**	-,288	-,017	-,279	-,292	-,118	-,396*	-,226
	Sig. (2-tailed)	,078	,003	,731		,000	,075	,916	,086	,072	,476	,013	,166
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaNok/EURO	Pearson Correlation	-,400*	-,457**	-,085	,624**	1	-,114	,045	-,112	-,379*	-,073	-,426**	-,111
	Sig. (2-tailed)	,012	,003	,605	,000		,491	,783	,497	,017	,658	,007	,501
	N	39	39	39	39	39	39	39	39	39	39	39	39
Delta10yNGB	Pearson Correlation	,282	,376*	,369*	-,288	-,114	1	,056	,870**	,141	,875**	,296	,206
	Sig. (2-tailed)	,082	,018	,021	,075	,491		,733	,000	,392	,000	,067	,208
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaNorInfla	Pearson Correlation	,360*	,302	,389*	-,017	,045	,056	1	-,035	,268	,102	,120	,189
	Sig. (2-tailed)	,024	,062	,015	,916	,783	,733		,832	,099	,536	,466	,249
	N	39	39	39	39	39	39	39	39	39	39	39	39
Delta10YGGB	Pearson Correlation	,216	,440**	,391*	-,279	-,112	,870**	-,035	1	,317*	,821**	,512**	,220
	Sig. (2-tailed)	,187	,005	,014	,086	,497	,000	,832		,050	,000	,001	,179
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaEuroInfla	Pearson Correlation	,129	,651**	,585**	-,292	-,379*	,141	,268	,317*	1	,170	,817**	,292
	Sig. (2-tailed)	,433	,000	,000	,072	,017	,392	,099	,050		,301	,000	,071
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaU.S.GB	Pearson Correlation	,479**	,457**	,403*	-,118	-,073	,875**	,102	,821**	,170	1	,290	,268
	Sig. (2-tailed)	,002	,003	,011	,476	,658	,000	,536	,000	,301		,073	,099
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaU.S.Infla	Pearson Correlation	,141	,643**	,439**	-,396*	-,426**	,296	,120	,512**	,817**	,290	1	,245
	Sig. (2-tailed)	,390	,000	,005	,013	,007	,067	,466	,001	,000	,073		,133
	N	39	39	39	39	39	39	39	39	39	39	39	39
DeltaPrimAluSold metric tonnes	Pearson Correlation	,530**	,522**	,399*	-,226	-,111	,206	,189	,220	,292	,268	,245	1
	Sig. (2-tailed)	,001	,001	,012	,166	,501	,208	,249	,179	,071	,099	,133	
	N	39	39	39	39	39	39	39	39	39	39	39	39

Appendix 8: Model summery and coefficients of the final risk exposure model

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,840[a]	,706	,661	622,567	2,210

a. Predictors: (Constant), DeltaPrimAluSold metric tonnes, DeltaNok/EURO, DeltaNorInfla, DeltaEuroInfla, DeltaPalu

b. Dependent Variable: DeltaEBITDA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	30676022,27	5	6135204,455	15,829	,000[b]
	Residual	12790444,03	33	387589,213		
	Total	43466466,31	38			

a. Dependent Variable: DeltaEBITDA

b. Predictors: (Constant), DeltaPrimAluSold metric tonnes, DeltaNok/EURO, DeltaNorInfla, DeltaEuroInfla, DeltaPalu

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	28,150	101,880		,276	,784					
	DeltaPalu	2,954	,695	,645	4,249	,000	,643	,595	,401	,387	2,583
	DeltaNok/EURO	-836,797	310,898	-,299	-2,692	,011	-,400	-,424	-,254	,721	1,387
	DeltaNorInfla	383,739	141,576	,277	2,710	,011	,360	,427	,256	,852	1,173
	DeltaEuroInfla	-1049,959	238,490	-,557	-4,403	,000	,129	-,608	-,416	,556	1,798
	DeltaPrimAluSold metric tonnes	6,231	2,589	,271	2,407	,022	,530	,386	,227	,705	1,418

a. Dependent Variable: DeltaEBITDA

Appendix 9: Frequencies statistic of the periodic changes in all risk exposures.

Statistics

		DeltaEBITDA	DeltaPalu	DeltaPel	DeltaNok/USD	DeltaNok/EURO	Delta10yNGB	DeltaNorInfla	Delta10YGGB	DeltaEuroInfla	DeltaU.S.GB	DeltaU.S.Infla	DeltaPrimAlu Sold metric tonnes
N	Valid	39	39	39	39	39	39	39	39	39	39	39	39
	Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean		-72,31	-28,9933	-,5377	,0656	,0244	-,07385	,06667	-,09772	-,0205	-,06308	-,01805	-6,67
Median		44,00	-34,0000	-1,2700	,0200	-,0200	-,10000	-,03400	-,13400	-,0500	-,08400	,06800	-12,00
Mode		-3831[a]	-979,76[a]	-16,24[a]	-,67[a]	,11	-,100	-,733[a]	-,877[a]	-,49[a]	-,855[a]	-4,846[a]	-57[a]
Std. Deviation		1069,511	233,44046	5,01543	,42910	,38252	,314522	,772695	,324037	,56780	,391990	1,189734	46,452
Variance		1143854,377	54494,450	25,155	,184	,146	,099	,597	,105	,322	,154	1,415	2157,807
Skewness		-,412	-1,783	-1,090	,474	1,468	,159	,587	-,079	-,913	,119	-,762	,047
Std. Error of Skewness		,378	,378	,378	,378	,378	,378	,378	,378	,378	,378	,378	,378
Kurtosis		4,836	6,213	3,502	-,127	5,076	,272	,378	,058	3,577	,027	9,363	,215
Std. Error of Kurtosis		,741	,741	,741	,741	,741	,741	,741	,741	,741	,741	,741	,741
Minimum		-3831	-979,76	-16,24	-,67	-,82	-,810	-1,333	-,877	-2,06	-,855	-4,846	-110
Maximum		3253	322,84	9,70	1,10	1,47	,670	2,166	,517	1,26	,859	4,007	95

a. Multiple modes exist. The smallest value is shown

Appendix 10: Model summery and coefficients of exposure model - all variables included

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,910[a]	,827	,757	527,352	2,216

a. Predictors: (Constant), DeltaU.S.Infla, DeltaNorInfla, DeltaPrimAluSold metric tonnes, Delta10yNGB, DeltaNok/EURO, DeltaPel, DeltaNok/USD, DeltaPalu, DeltaEuroInfla, DeltaU.S.GB, Delta10YGGB

b. Dependent Variable: DeltaEBITDA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35957760,46	11	3268887,314	11,754	,000[b]
	Residual	7508705,852	27	278100,217		
	Total	43466466,31	38			

a. Dependent Variable: DeltaEBITDA

b. Predictors: (Constant), DeltaU.S.Infla, DeltaNorInfla, DeltaPrimAluSold metric tonnes, Delta10yNGB, DeltaNok/EURO, DeltaPel, DeltaNok/USD, DeltaPalu, DeltaEuroInfla, DeltaU.S.GB, Delta10YGGB

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1,368	93,349		,015	,988					
	DeltaPalu	1,946	,729	,425	2,671	,013	,643	,457	,214	,253	3,954
	DeltaNok/EURO	-1084,662	326,643	-,388	-3,321	,003	-,400	-,538	-,266	,469	2,133
	DeltaNorInfla	332,404	131,698	,240	2,524	,018	,360	,437	,202	,707	1,415
	DeltaEuroInfla	-905,240	319,495	-,481	-2,833	,009	,129	-,479	-,227	,222	4,497
	DeltaPrimAluSold metric tonnes	5,519	2,235	,240	2,469	,020	,530	,429	,197	,679	1,473
	DeltaPel	32,342	27,039	,152	1,196	,242	,380	,224	,096	,398	2,513
	DeltaNok/USD	-126,948	318,980	-,051	-,398	,694	-,286	-,076	-,032	,391	2,560
	Delta10yNGB	-2005,418	785,311	-,590	-2,554	,017	,282	-,441	-,204	,120	8,336
	Delta10YGGB	-121,585	729,170	-,037	-,167	,869	,216	-,032	-,013	,131	7,628
	DeltaU.S.GB	2072,283	568,841	,760	3,643	,001	,479	,574	,291	,147	6,794
	DeltaU.S.Infla	-94,468	156,209	-,105	-,605	,550	,141	-,116	-,048	,212	4,719

a. Dependent Variable: DeltaEBITDA

Appendix 11: Correlations - normal market conditions

Correlations

		DeltaPalu	DeltaNok/USD	DeltaNok/EURO	DeltaEuroInfla	DeltaPrimAlu Sold metric tonnes	DeltaPel	Delta10yNGB	DeltaNorInfla	Delta10YGGB	DeltaU.S.GB	DeltaU.S.Infla
DeltaPalu	Pearson Correlation	1	-,357	-,288	,399*	,173	,480*	,282	,138	,339	,303	,518**
	Sig. (2-tailed)		,074	,154	,043	,399	,013	,162	,501	,090	,133	,007
	N	26	26	26	26	26	26	26	26	26	26	26
DeltaNok/USD	Pearson Correlation	-,357	1	,512**	-,181	-,213	-,005	-,163	-,106	-,105	,057	-,375
	Sig. (2-tailed)	,074		,007	,376	,296	,979	,426	,606	,609	,781	,059
	N	26	26	26	26	26	26	26	26	26	26	26
DeltaNok/EURO	Pearson Correlation	-,288	,512**	1	-,307	-,097	-,026	,146	-,096	,200	,200	-,087
	Sig. (2-tailed)	,154	,007		,127	,639	,899	,477	,639	,326	,327	,673
	N	26	26	26	26	26	26	26	26	26	26	26
DeltaEuroInfla	Pearson Correlation	,399*	-,181	-,307	1	-,085	,543**	-,008	-,229	,128	,074	,663**
	Sig. (2-tailed)	,043	,376	,127		,680	,004	,967	,261	,533	,718	,000
	N	26	26	26	26	26	26	26	26	26	26	26
DeltaPrimAluSold metric tonnes	Pearson Correlation	,173	-,213	-,097	-,085	1	,240	,190	-,078	,202	,120	,239
	Sig. (2-tailed)	,399	,296	,639	,680		,238	,352	,704	,322	,559	,239
	N	26	26	26	26	26	26	26	26	26	26	26
DeltaPel	Pearson Correlation	,480*	-,005	-,026	,543**	,240	1	,220	-,264	,331	,317	,523**
	Sig. (2-tailed)	,013	,979	,899	,004	,238		,279	,193	,099	,115	,006
	N	26	26	26	26	26	26	26	26	26	26	26
Delta10yNGB	Pearson Correlation	,282	-,163	,146	-,008	,190	,220	1	,127	,898**	,909**	,238
	Sig. (2-tailed)	,162	,426	,477	,967	,352	,279		,535	,000	,000	,242
	N	26	26	26	26	26	26	26	26	26	26	26
DeltaNorInfla	Pearson Correlation	,138	-,106	-,096	-,229	-,078	-,264	,127	1	,032	,164	-,048
	Sig. (2-tailed)	,501	,606	,639	,261	,704	,193	,535		,878	,425	,815
	N	26	26	26	26	26	26	26	26	26	26	26
Delta10YGGB	Pearson Correlation	,339	-,105	,200	,128	,202	,331	,898**	,032	1	,911**	,308
	Sig. (2-tailed)	,090	,609	,326	,533	,322	,099	,000	,878		,000	,126
	N	26	26	26	26	26	26	26	26	26	26	26
DeltaU.S.GB	Pearson Correlation	,303	,057	,200	,074	,120	,317	,909**	,164	,911**	1	,248
	Sig. (2-tailed)	,133	,781	,327	,718	,559	,115	,000	,425	,000		,222
	N	26	26	26	26	26	26	26	26	26	26	26
DeltaU.S.Infla	Pearson Correlation	,518**	-,375	-,087	,663**	,239	,523**	,238	-,048	,308	,248	1
	Sig. (2-tailed)	,007	,059	,673	,000	,239	,006	,242	,815	,126	,222	
	N	26	26	26	26	26	26	26	26	26	26	26

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 12: Model summery and coefficients - normal market conditions

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,878[a]	,772	,592	375,296	2,173

a. Predictors: (Constant), DeltaPrimAluSold metric tonnes, DeltaNorInfla, DeltaNok/EURO, DeltaU.S.Infla, Delta10yNGB, DeltaPel, DeltaPalu, DeltaNok/USD, DeltaEuroInfla, Delta10YGGB, DeltaU.S.GB

b. Dependent Variable: DeltaEBITDA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6666355,066	11	606032,279	4,303	,006[b]
	Residual	1971860,050	14	140847,146		
	Total	8638215,115	25			

a. Dependent Variable: DeltaEBITDA

b. Predictors: (Constant), DeltaPrimAluSold metric tonnes, DeltaNorInfla, DeltaNok/EURO, DeltaU.S.Infla, Delta10yNGB, DeltaPel, DeltaPalu, DeltaNok/USD, DeltaEuroInfla, Delta10YGGB, DeltaU.S.GB

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-107,939	94,571		-1,141	,273					
	DeltaPalu	2,486	,722	,612	3,443	,004	,459	,677	,440	,516	1,936
	DeltaPel	-28,644	41,293	-,133	-,694	,499	,043	-,182	-,089	,444	2,252
	DeltaNok/USD	132,728	333,911	,088	,397	,697	-,012	,106	,051	,331	3,018
	DeltaNok/EURO	-629,582	410,454	-,301	-1,534	,147	-,224	-,379	-,196	,423	2,362
	Delta10yNGB	-1339,499	750,437	-,726	-1,785	,096	,149	-,431	-,228	,099	10,149
	DeltaNorInfla	-50,688	181,190	-,044	-,280	,784	,310	-,075	-,036	,658	1,519
	Delta10YGGB	-1019,550	789,826	-,519	-1,291	,218	,114	-,326	-,165	,101	9,919
	DeltaEuroInfla	-1015,753	414,581	-,596	-2,450	,028	-,281	-,548	-,313	,275	3,634
	DeltaU.S.GB	2153,887	818,633	1,304	2,631	,020	,260	,575	,336	,066	15,063
	DeltaU.S.Infla	70,023	241,267	,068	,290	,776	-,023	,077	,037	,293	3,413
	DeltaPrimAluSold metric tonnes	4,154	2,215	,295	1,875	,082	,363	,448	,239	,661	1,514

a. Dependent Variable: DeltaEBITDA

Appendix 13: Model summery and coefficients - risk exposure model - normal market conditions.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,797[a]	,636	,545	396,563	2,295

a. Predictors: (Constant), DeltaPrimAluSold metric tonnes, DeltaEuroInfla, DeltaNok/USD, DeltaPalu, DeltaNok/EURO

b. Dependent Variable: DeltaEBITDA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5492963,596	5	1098592,719	6,986	,001[b]
	Residual	3145251,519	20	157262,576		
	Total	8638215,115	25			

a. Dependent Variable: DeltaEBITDA

b. Predictors: (Constant), DeltaPrimAluSold metric tonnes, DeltaEuroInfla, DeltaNok/USD, DeltaPalu, DeltaNok/EURO

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1,945	79,790		,024	,981					
	DeltaPalu	2,725	,639	,671	4,261	,000	,459	,690	,575	,735	1,360
	DeltaNok/USD	549,803	247,908	,365	2,218	,038	-,012	,444	,299	,671	1,490
	DeltaNok/EURO	-778,696	340,039	-,372	-2,290	,033	-,224	-,456	-,309	,689	1,452
	DeltaEuroInfla	-981,441	261,541	-,576	-3,753	,001	-,281	-,643	-,506	,772	1,295
	DeltaPrimAluSold metric tonnes	3,384	1,991	,240	1,700	,105	,363	,355	,229	,913	1,095

a. Dependent Variable: DeltaEBITDA