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Hedging strategies within the aluminum market

An analysis of forecast adjusted strategies with the persepctive of a Norwegian entity

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Abstract

This thesis examines the effectiveness of static and selective hedging strategies in the aluminum market. Additionally, the thesis highlights the outcome from the perspective of a Norwegian entity, particularly focusing on the impact of the USD/NOK exchange rate. By applying forecast adjustments to static strategies such as MVHR and Naive HR, we develop selective strategies. We then analyze these to determine whether they provide any additional benefits. Employing a quantitative analytical framework, the study uses regression analysis to calculate the HR and adjust the MVHR and NHR based on three forecast types: analyst predictions, naive forecasts, and seasonal and trend variation forecasts. This methodology is thoroughly tested for data validity, including tests for stationarity, cointegration, and normal distribution.

The research reveals that hedging strategies adjusting for analytics market forecasts offer the best risk-adjusted returns, as indicated by higher Sharpe ratios. Additionally, the research presents that selective strategies does not necessarily improve hedging effectiveness, when compared to static strategies. We also find that the results differ when considering the impact of currency exchange rates. This variation is notable in terms of both the Sharpe ratio and hedging effectiveness, underscoring the significant role currency fluctuations play in determining the optimal approach for hedging.

This thesis contributes to the field by presenting a novel approach to hedging strategy formulation, incorporating forecast-based adjustments and currency fluctuations. It provides empirical evidence on the effectiveness of these adjusted strategies in managing market risks.

This research underscores the importance of incorporating dynamic forecast adjusted strategies, particularly for entities in the aluminum market operating across different currencies. It presents a comprehensive view of how tailored hedging approaches can effectively manage the inherent risks in commodity trading. The research offers valuable insights for both theoretical understanding and practical application in risk management.

Table of Contents

List of figures

List of tables

1. Intro

Over the last century, aluminum has undergone a remarkable transformation, evolving from minimal production to becoming the world's second most mined metal (Sverdrup et al., 2015). Aluminum today is used in more products than ever, only since 2000 the market for aluminum products has doubled (International Aluminium Institute, n.d.). Its universal presence in daily life is evident across numerous applications - from construction materials and transportation vehicles to consumer electronics and packaging (Hydro, 2021).

Since 1971, the global demand for primary aluminum has increased nearly sixfold. There are no signs this growth is declining. Actually, forecasts considering ongoing population and economic growth, project a 75% rise in aluminum demand by 2060, relative to 2017 numbers. This anticipated growth exceeds the projected demand for other key materials like steel and cement (International Energy Agency, 2019). Such demand dynamics stems from aluminum's versatile properties, in combination with the global push towards sustainability. Aluminum's recycling process, requiring just 5% of the energy used for initial production and offer infinite recycling potential without quality degradation. When you also factor in the abundance of the material on earth it aligns well with environmental sustainability goals (International Aluminium Institute, n.d.). In economic terms, the global aluminum market was valued at 150 billion USD in 2021 and is anticipated to escalate to 255 billion USD by 2030 (Straits research, 2022).

This remarkable growth trajectory is predominantly propelled by robust construction activities, particularly in the Asia-Pacific region, and the transportation sector. Notably the automotive industry demand for aluminum increased as they recognized its advantages in terms of much-reduced weight. This shift enhances vehicle efficiency by lowering fuel consumption and emissions and also aligns with global environmental and efficiency standards.

However, the growing reliance on aluminum is not without its challenges, particularly in terms of market volatility. Recent global events have starkly illustrated this volatility. During the COVID-19 pandemic, aluminum prices experienced significant fluctuations due to supply chain disruptions and shifts in market dynamics. Additionally, the ongoing conflict in Ukraine has further exacerbated this uncertainty, with geopolitical tensions once again contributing to price volatility and supply chain disruptions.

To counter these risks, effective risk management strategies, such as price hedging, are crucial. Hedging provides a measure of financial stability in the face of unpredictable aluminum market movements, ensuring that industries dependent on this vital metal can navigate the turbulent economic landscape. For a Norwegian entity, there is the added currency risk. Seeking to mitigate price risk in a volatile aluminum market, it is common to hedge through buying or selling the commodity in futures contracts. As this is done in an international market, and transactions are denominated in USD, these activities can expose the entity to currency fluctuations between the Norwegian Krone (NOK) and the US Dollar (USD). Thereby exposing them to further risk and potentially diminishing the effect of the initial hedge.

Hedging strategies integrate the dual objectives of reducing risk and leveraging expected values. The ideal hedging strategy is one that not only limits costs but also optimizes the efficiency of risk management practices. The specific goals of a hedging strategy can vary significantly among different entities. These variations are influenced by each entity's unique risk and return preferences. Thus, the concept of an “optimal” hedging strategy is inherently dependent on the individual objectives with risk management, whether it be minimizing risk or maximizing utility. Furthermore, it is essential to acknowledge that the optimal hedging strategy is influenced not only by internal factors, but also by external factors. Including the broader market conditions in which the firm operates, underscoring the need for a strategy that carefully balances these internal objectives with external market realities.

There are several methodologies that target the reduction of price risk. Static hedging strategies employ a consistent correlation between spot and future prices. However, the search for a universally superior hedging strategy, one that consistently outperforms a naive hedging approach, remains elusive. In contrast, selective hedging strategies offer the flexibility of modifying hedge positions in terms of timing and volume based on market insights. It has been observed that selective hedging, particularly when informed by accurate market forecasts, can not only enhance profitability but also effectively reduce price risk.

Research question

How do various hedging strategies perform in managing the volatility of the aluminum market, particularly from the perspective of a Norwegian entity? This study aims to investigate and compare various hedging approaches, focusing on assessing their effectiveness in navigating market uncertainties. An aspect of the Norwegian perspective is to understand how the integration of a currency element influences the effectiveness of these strategies.

2. Theory

2.1 What is hedging and why should we hedge?

In the evolving world of finance, where global markets are intertwined and susceptible to rapid changes, strategies to mitigate risks become vital. The recent economic disruptions, such as the prolonged effects of the COVID-19 pandemic, the war in Ukraine and geopolitical uncertainties, have only heightened the importance of understanding and implementing effective risk management practices. One of the most widely recognized and utilized methods in this realm is hedging.

2.1.1 Stability

Hedging, in its simplest definition, is an investment strategy employed to offset potential losses that may be incurred by another investment. By implementing hedging techniques, investors aim to protect themselves from undesirable market fluctuations that could harm their financial positions (Hull, 2012). Examples of hedging can be observed in the commodities sector. If the price of a commodity falls, gains from futures contracts can counterbalance losses in the main business operations. Conversely, if commodity prices surge, potential losses from futures contracts are offset by increased profits from primary business activities. This balancing act, when flawlessly executed, culminates in what is referred to as a "perfect hedge" (Johnson, 1960).

The concept of a perfect hedge implies total risk neutralization, where the asset being safeguarded, and the hedging instrument possess an inverse correlation. In such an ideal scenario, any depreciation in the primary asset's value is precisely matched by an appreciation in the hedging tool, ensuring the combined worth of both remains constant irrespective of market dynamics (Hull, 2012; Johnson, 1960). However, orchestrating a perfect hedge is a challenging endeavor. The process demands meticulous calibration, often accompanied by inherent costs. As a result, most hedges in the real-world focus on risk reduction rather than its absolute elimination.

Hedging can provide a more predictable financial environment. By hedging against volatile prices or rates, businesses can more accurately predict future costs and revenues, making financial planning and budgeting more effective. Regular cash flows are critical for operational activities, such as payroll, rent, and reinvestment. By hedging against adverse movements, companies ensure that they have a consistent cash flow, which is especially vital for businesses with thin profit margins. If a company can hedge effectively against raw material price increases, it can maintain its product prices without frequent changes, providing a competitive advantage.

2.1.2 Short and long hedge

A common hedging strategy often used in the commodities sector is maintaining a short position in the market. This involves taking a short position in futures contracts, effectively selling futures contracts on the commodity they produce (Hull, 2012). Commodity sellers naturally have a long position in their markets because they own the commodity. Thus, they benefit from price rises and suffer from price drops (Johnson, 1960). To counteract this exposure, sellers short futures contracts, effectively locking in a certain price for future sales. It's a practical risk management strategy, allowing companies to safeguard against adverse price fluctuations and stabilize their future revenues.

The opposite of a short hedge is a long hedge. This strategy involves taking a long position in futures contracts, effectively committing to purchase a commodity at a set price in the future. Typically, entities that are expected to buy a commodity in the future – like manufacturers or processors – employ a long hedge to lock in a price (Hull, 2012). This ensures protection against potential price increases, securing their procurement costs and allowing for consistent financial planning.

2.1.3 Hedging in different currencies

While hedging is fundamentally a tool to manage and mitigate risks, it doesn't come without its own set of challenges, which if not addressed, can lead to worse outcomes (Hull, 2012). One prominent issue arises when the hedging instrument and the primary asset have a currency mismatch. For instance, a Norwegian aluminum producer has to present their financial statements in NOK, which exposes them to currency risk, even though the price risk is reduced. Essentially, while they may have protected themselves against a decline in aluminum prices, they are now vulnerable to unfavorable foreign exchange movements. This additional layer of complexity not only requires monitoring global aluminum prices but also monitoring macroeconomic factors affecting the USD/NOK exchange rate. Thus, a strategy meant to shield against risks in one arena can, without careful management, introduce new vulnerabilities in another.

2.2 Futures

"Futures contract is an agreement between two parties to buy or sell an asset at a certain time in the future for a certain price" (Hull, 2012, p. 7). From the definition it's evident that futures contracts bear resemblances to forward contracts. However, there are relevant distinctions between the two. The main difference is the trading location. Unlike forward contracts, which are typically private agreements between parties, futures contracts are typically traded on organized exchanges. This exchange-traded nature means that certain features of the contract are standardized, such as the asset, the contracted size, delivery arrangements and asset quality (Hull, 2012). This facilitates easier trading. Different exchanges and commodities of course have different degrees of standardizations.

The futures market offers a centralized platform for participants to enter contracts and commit to buy or sell a specific commodity at an agreed price in the future. Serving as a tool for price discovery and risk mitigation in the face of volatile commodity prices. The futures contracts attract two primary players: hedgers and speculators. Though operating within the same market, their underlying motivations and interests diverge considerably.

2.2.1 Price determination of commodity futures contracts

Commodity futures contracts are priced by the market, which means that the price is determined by the supply and demand for the contract. The price is also influenced by a number of other factors, including the current spot price of the commodity, the cost of carry and expectations about the future supply and demand (Hull, 2022).

The spot price is the current market price of the commodity, and it is the price that buyers and sellers are willing to pay and accept for immediate delivery. The cost of carry is the cost of storing and financing the commodity until the delivery date. This includes the cost of storage, insurance, and interest (Luenberger, 2009).

Expectations about future supply and demand also play a role in determining the price of a futures contract. If market participants expect that the supply of a commodity will be tight in the future, they will be willing to pay a premium for a futures contract that guarantees delivery of the commodity at a fixed price. Conversely, if market participants expect that the supply of a commodity will be abundant in the future, they will be less willing to pay for a futures contract (Bodie et al., 2018).

2.2.2 Hedgers vs speculators

Commodity trading theorists traditionally view hedgers as dealers in physical commodities, seeking to mitigate the price risks of holding a long position. By participating in the futures market, they aim to lock in a price today for a transaction that will occur in the future, thus protecting themselves from unfavorable price movements. Their primary objective is not necessarily to generate profit but to achieve predictability, by reducing risk.

Contrasting the hedgers are the speculators, a group of market participants driven by different motivations. Speculators willingly accept the price risk that hedgers seek to avoid, with the intent of profiting from future price changes. Their decisions are often based on market analyses, forecasts, or even hunches about future events. Often, they don't have any interest in the physical commodities at all, but they play a crucial role in providing liquidity to the market (Bodie et al., 2018).

2.2.3 Institutional aspects

In futures markets, the institutional structures play a pivotal role in risk mitigation and market efficiency. Clearing houses intervenes as an intermediary between contract parties, effectively becoming the counterparty to both the buyer and seller. Their objective is to ensure that the obligations of a futures contract are met even if one party defaults. To further manage the risks associated with price fluctuations, the futures market institutes margin requirements.

Participants are mandated to deposit an initial margin, a form of collateral, to initiate a position. Positions are marked to market daily, which can lead to a decline in an account if there are adverse price movements. Should this decline breach a specified maintenance margin, a margin call is issued, requiring the deposit of additional funds. Finally, while many futures contracts require physical delivery of the underlying item at maturity, others use a cash settlement approach, in which the difference between the futures and spot price is resolved in cash, eliminating the requirement for physical exchange (Bodie et al., 2018).

2.3 Cost-of-Carry and Risk Premium Hypotheses

When exploring the factors of futures pricing for aluminum, two main theories stand out: the Cost-of-Carry and the Risk Premium Hypotheses. The Cost-of-Carry theory suggests that the futures price of a storable commodity, like aluminum, is based on its spot price plus carrying costs up to contract maturity. These carrying costs include storage, financing, insurance, and are adjusted for any benefits like the convenience yield (Working, 1948, 1949). Mathematically, the relationship can be delineated as follows:

$$F_t(T) = S_t + (r + u - y)(T - t) \tag{1}$$

where *r* represents the risk-free interest rate, *u* the storage cost per unit time, *y* the convenience yield, and $T - t$ the time to maturity of the futures contract.

Conversely, the Risk Premium Hypothesis introduces the notion of an inherent premium embedded within the futures price, to compensate investors for the risk undertaken due to the uncertainty of future spot prices (Fama & French, 1987). The expected return of a futures contract in this context is not merely the cost of carry, but also an additional risk premium $\boldsymbol{\pi}$, reflective of the market's risk aversion. The futures price under this hypothesis is thus represented by:

$$F_t(T) = S_t + E_t[(S_T - S_t)] + \pi_t(T) \tag{2}$$

where $E_t[(S_T - S_t)]$ is the expected change in the spot price and $\pi_t(T)$ is the risk premium at time t for delivery at time T.

The interplay between these hypotheses is pivotal when considering hedging strategies for aluminum. The Cost-of-Carry Hypothesis suggests a more deterministic approach based on observable costs and benefits, whereas the Risk Premium Hypothesis accounts for market sentiment and the volatility of expectations regarding future spot prices. Notably, the empirical validation of these hypotheses has been subject to extensive scrutiny, with studies indicating that while the Cost-of-Carry can explain a significant portion of the futures price, risk premiums cannot be dismissed, especially in markets characterized by heightened uncertainty (McAleer et al., 2000).

The implications of these hypotheses extend to the hedging practices of firms involved in the production, consumption, or trading of aluminum. For instance, a firm anticipating an increase in aluminum prices due to market factors may engage in futures contracts based on the Cost-of-Carry model to lock in current prices plus carrying costs. Conversely, in a market anticipating high volatility, the same firm might be inclined to pay a premium over the Cost-of-Carry for futures contracts, incorporating the risk premium into their hedging strategy.

In conclusion, a comprehensive hedging strategy for aluminum must consider both the Cost-of-Carry and Risk Premium Hypotheses, while remaining adaptable to the insights provided by ongoing empirical research. Such a strategy should reflect both today's market conditions and future changes to protect against unpredictable prices and improve financial stability.

2.4 Modern Portfolio Theory

The optimal portfolio, introduced by Harry Markowitz, refers to the specific combination of assets that yields the highest possible return for a given level of risk or, conversely, the lowest risk for a predetermined expected return. In essence, it represents the most efficient allocation of assets to achieve the desired balance between risk and reward (Markowitz, 1991).

Determining this optimal mix is a multifaceted process that hinges on several key factors. Firstly, one must consider the risk-return trade-off, a principle suggesting that higher potential returns typically come with increased risk. This relationship is visually represented by the efficient frontier, a curve plotting the maximum expected return for each risk level. Portfolios that lie on this curve are deemed efficient, while those that don't are sub-optimal.

Another pivotal element is the correlation between the assets. Perfectly correlated assets move in sync, offering no diversification benefits. In contrast, negatively correlated assets move in opposite directions, providing a potential risk-buffering effect (Markowitz, 1991).

The true power of the optimal portfolio lies in harnessing these correlations to minimize overall risk. Additionally, the introduction of a risk-free asset, like a short-term government bond, shifts the focus to the tangency portfolio, which touches a straight line drawn from the risk-free rate and offers the highest risk-adjusted return. It's worth noting that the optimal portfolio is not a one-size-fits-all solution. It varies among investors based on individual risk tolerance, financial goals, and investment horizons (Markowitz, 1991).

2.5 Hedging strategies

Futures contracts are utilized as an insurance for the risk of prices increasing or decreasing in an unfavorable way, whether you act as a seller or buyer. For instance, if you buy a commodity at a certain spot price with the intent of processing it and selling it, you face the risk of the spot price increasing. An increase in the procurement cost, directly affects your profit margin in a negative direction. The opposite applies if you are a seller of a commodity. The gain or loss of an unhedged portfolio is simply the future spot price (S_2) subtracted by the current spot price (S_1) (Nakajima & Hamori, 2022).

$$r_{unhedged\ portfolio} = (S_2 - S_1) \tag{3}$$

$$r_{hedged\ portfolio} = (S_2 - S_1) - (F_2 - F_1) \tag{4}$$

The hedged portfolios return includes the difference between the futures prices in the respective time periods. When the differences in spot prices are equal to the differences in futures prices, meaning $r = 0$, the hedge is perfect, because the positions offset each other.

In hedging, when the changes in spot and futures prices do not move in perfect tandem, basis risk arises. This means that the return on the hedged portfolio may not be perfectly offset, resulting in a non-zero net position. Basis refers to the difference between the spot price of the underlying asset and the futures price. Basis risk can be attributed to various factors, such as the misalignment in price movements between the underlying and its futures contract, differing maturity dates, or any other discrepancies between the specifications of the hedged asset and the hedging instrument (Hull, 2022).

The traditional hedging theory stated that you could either be fully hedged or unhedged, because you have futures in the same risk/return level as the asset. Johnson (1960) and Stein (1961) applied the Modern Portfolio Theory (MPT) to explain why it is possible to reach a portfolio with both hedged and unhedged stocks. Markowitz' portfolio theory aims to maximize returns for a given level of risk or minimize risk for a given level of return (Ederington, 1979, p. 89). Ederington furthered this by holding the spot exposure fixed, and the level of exposure in the hedging position as uncertain.

Hedge ratio (θ) is the relationship between the underlying asset and the size of a derivative instrument which is hedging the asset. It quantifies the relationship between the change in the value of the derivative position and the change in the value of the underlying asset or portfolio. It is described by dividing the value of the hedged position with the total position value. (*Hedge Ratio (Delta) Definition | Nasdaq*, n.d.)

$$Hedge\ Ratio\ (\theta) = \frac{Hedged\ position}{Total\ value\ position} \tag{5}$$

Given that the underlying assets are held constant, changes in the hedged position determine how much of the base risk is reduced. Johnson (1960) enlightens that the main objective of is to combine such a hedge that fits the risk profile. The following equation illustrates that the expected return of a hedged portfolio is a combination of the change in the spot price subtracted by the weighted change in the futures prices (Hamori & Nakajima, 2022, p. 89):

$$E(R) = \Delta s_{t+1} - \theta \Delta f_{t+1} \tag{6}$$

In the market s, the variance of price change represented as σ_s^2, is equivalent to the variance of return, often referred to as "price risk", when holding one unit in market. This holds true from t_1 to t_2, as the absolute value of the actual return resulting from price change during this period is equal to the absolute value of the price change itself. Equally, the same theory holds for the futures contract market. The symbol $Cov_{f,s}$ denotes the covariance of the price changes in spot and futures prices, while θ_t^2 is used to calculate the variance of futures relative to the weighting of the hedge. The total variance of a hedged portfolio is described by (Nakajima & Hamori, 2022, p. 89):

$$Var(R) = Var(\Delta s_{t+1}) + \theta_t^2 Var(\Delta f_{t+1}) - 2\theta_t Cov(\Delta s_{t+1}, \Delta f_{t+1}) \tag{7}$$

2.5.1 Hedging effectiveness

$$HE = 1 - \left[\frac{Variance_{HedgedPortfolio}}{Variance_{UnhedgedPortfolio}}\right] \tag{8}$$

The evaluation of hedging effectiveness involves comparing the risk of an unhedged portfolio with the minimum risk achievable through a portfolio comprising both spot and forward securities. This assessment quantifies the percentage reduction in variance of the hedged portfolio relative to the unhedged counterpart. In the ideal scenario where the futures contract entirely eradicates risk, resulting in HE = 1, there is a 100% reduction in variance. Conversely, HE = 0 signifies that hedging with the futures contract fails to mitigate risk. A higher value of HE indicates a more effective hedging performance (Cotter & Hanly, 2015; Ederington, 1979).

Despite its limitations, the inclusion of variance as the standard measure of risk in finance is imperative. One notable drawback of variance lies in its implicit accommodation of investors characterized by infinite risk aversion. Nevertheless, its integration remains pivotal in assessing hedging effectiveness (Cotter & Hanly, 2015).

2.6 Optimal Hedge Ratio

The optimal hedge ratio (OHR) is defined as the ratio of futures positions relative to the spot position that reduces variance to its minimum (Nakajima & Hamori, 2022). We can distinguish between two techniques when determining what is ideal in a hedge strategy. The first, inspired by Johnson (1960) and others, follows a return volatility model emphasizing variance minimization. This methodology primarily aims at risk reduction, leading to strategies known as the Minimum Variance Hedge Ratio (MVHR). While its straightforward computation and interpretation make it popular, it's not without limitations. The method is often criticized for its exclusive focus on risk, neglecting factors such as risk aversion levels and expected returns. Moreover, it fails to distinguish between short and long hedgers, overlooking potential differences in their risk perceptions.

The alternative approach centers on maximizing expected utility, which is a combined function of risk and expected return. Here, risk aversion plays a crucial role in determining the optimal hedge strategy (Cotter & Hanly, 2010).

2.6.1 Minimum Variance Hedge Ratio (MVHR)

Building upon the principals of Markowitz' Portfolio Theory (MPT), Johnson developed a risk minimizing hedge ratio. This is achieved by taking the partial derivative of equation (5) with respect to θ. By setting this partial derivative equal to zero and subsequently solving for θ, the optimal risk-minimizing portfolio is determined:

$$MVHR = \frac{Cov(\Delta s_{t+1}, \Delta f_{t+1})}{Var(\Delta f_{t+1})} \quad \text{or} \quad MVHR = \rho \frac{\sigma_S}{\sigma_F} \tag{9}$$

The formula is based on the covariance of the spot and futures returns divided by the variance of the futures return (Nakajima & Hamori, 2022).We can also simplify this by multiplying the correlation coefficient with the standard deviation of ΔS divided by ΔF (Hull, 2022, p. 57). Hence, a multitude of factors can potentially influence this ratio. The obvious ones are changes in the standard deviations, where for instance an increase in σ_S will increase MVHR, implying that additional futures contracts are needed to keep the hedged position, ceteris paribus. This can be due to significant price movements due to recent news, market events etc. A change in the correlation coefficient will also greatly impact the MVHR. It should be underscored that the MVHR inherently assumes an infinite risk aversion, with the primary objective being the minimization of risk rather than the maximization of returns (Chen et al., 2003).

2.6.2 Utility based hedge ratio

The Utility-Based Hedge Ratio (UBHR) offers a nuanced approach compared to the Minimum Variance Hedge Ratio (MVHR) by factoring in an individual's risk preferences. As outlined by Cotter and Hanly (2015, p. 719), the ratio assumes that an individual has a quadratic utility function. Estimating the parameters accurately, especially the risk aversion coefficient is crucial, but it introduces complexity that some might deem unnecessary.

$E(\Delta f_{t+1})$ describes the expected return in the futures market, λ is the coefficient of risk aversion. $Var(\Delta f_{t+1})$ is the variance in the return in the futures market and $Cov(\Delta s_{t+1}, \Delta f_{t+1})$ is the covariance of the spot and futures returns. The first part of the equation captures the risk preferences of the individual, while the latter part is identical to the MVHR.

$$Utility\ Based\ Hedge\ Ratio = \frac{-E(\Delta f_{t+1})}{2\lambda Var(\Delta f_{t+1})} + \frac{Cov(\Delta s_{t+1}, \Delta f_{t+1})}{Var(\Delta f_{t+1})} \tag{10}$$

2.6.3 Naive hedge ratio

The naive hedge ratio is a straightforward hedging approach that adopts a 1:1 ratio, implying that for every unit of exposure in the spot market, an equivalent but opposite position is taken in the futures market (Brooks, 2019). This simplistic strategy is often employed as a benchmark against more intricate hedging techniques. While its primary advantage lies in its simplicity, making it easy to implement and understand, it operates under the assumption that futures and spot prices move in perfect tandem. However, in real-world scenarios, this may not always hold true, potentially leading to imperfect hedging outcomes. From a theoretical viewpoint, one might assume that the optimal hedging method would be superior to the naive strategy. However, many empirical research findings suggest a different narrative (Wang et al., 2015).

2.6.4 No Hedge

An alternative course of action is to abstain from hedging altogether. This approach entails full exposure to the spot price and its inherent volatility. This strategy is commonly employed as a performance benchmark in sectors where participants often choose to not hedge their assets, such as within the energy sector. The intuition is anchored in the classic risk-return trade-off: hedging, though reducing potential risks, also diminishes the prospective returns from bearing those very risks. By not hedging, market participants potentially position themselves for higher returns, fully acknowledging the accompanying risk (Cotter & Hanly, 2015).

2.7 Selective Hedging Strategies

Selective hedging strategies symbolize an advanced tier of risk management within financial markets. These strategies are grounded in the principle that the market actor autonomously determines when and to what extent the underlying assets are to be hedged. This autonomy implies that hedging decisions are made based on the actor's current market view, allowing for a degree of speculation within the hedging strategy itself. Such an approach contrasts with traditional hedging, which may employ a uniform strategy across all assets without regard for the individual market outlook at any given time (Stulz, 1996).

Selective hedging allows decision makers to customize their hedging actions. The hedging is depending upon anticipated future price movements, incorporating a speculative element that aligns with the trader’s market perception. This level of customization facilitates a dynamic approach to safeguarding assets against the inevitable fluctuations of market prices (Stulz, 1996).

2.7.1 Interplay of Forecasts and Futures Market Investments

The utilization of futures contracts as instruments for price insurance is considerably impacted by the precision and dependability of market forecasts. These forecasts are not static, they reflect the evolving market sentiment and the strategic foresight of the investor. They act as the compass that guides investors on the optimal moments to engage in hedging and when it might be wise to refrain.

The contrast faced by market participants in the futures market: to hedge, thereby locking in current prices against future declines, or not to hedge, potentially benefiting from an upswing in prices. The selective hedging strategy thus incorporates an element of speculation, as it is predicated on the market view held by the actor at any given point, a clear contrast to a one-size-fits-all hedging approach (Adam et al., 2017; Luiz Rossi, 2013).

2.7.2 Why develop forecasts

The foresight provided by accurate forecasts is crucial, offering a way to navigate through market uncertainties. The distinction between short-term and long-term forecasts highlights their varying applications, from tactical maneuvers to strategic planning. The former closely tied to the flow of price fluctuations, while the latter extends to the broader trends, seasonal variations, market forces, and political landscapes that shape the economic view over an extended period (Hanke & Wichern, 2014).

Forecasts are also categorized by their foundational inputs. There are qualitative forecasts, rooted in the nuanced judgments of experienced professionals, and statistical forecasts, derived from the rigorous application of mathematical methods. The best forecasts often result from an union of these two approaches, where statistical projections are fine-tuned with qualitative assessments to reflect a more accurate picture of the future (Sanders, 2017, p. 56).

Historical analyses highlights significant enhancements in corporate performance, particularly in cost reduction, attributed to the development and application of forecasting models (Sanders, 2017, p. 6). Furthermore, empirical evidence suggests that statistical forecasts outperform their qualitative counterparts by 18.1% in accuracy, underscoring the tangible benefits of incorporating data-driven insights into the forecasting process (Sanders, 2017, p. 54).

These findings underscore the critical nature of forecasting in corporate strategy. By leveraging both qualitative and quantitative data, organizations can navigate future uncertainties with greater confidence, positioning themselves to respond proactively to the ever-changing market dynamics.

2.7.3 Evaluating Forecast Precision

A forecast's worth is evaluated by its precision, necessitating a suite of measures to assess its accuracy. This subsection introduces the notion of an error margin, a critical concept in forecast evaluation. Various methods, including but not limited to standard deviation and relative deviation, are discussed to understand their role in quantifying forecast accuracy. These methods provide a statistical basis for the evaluation, offering a way to measure the dispersion and reliability of forecasts.

2.7.4 Measuring the Accuracy of Forecasts

Evaluating the precision of predictions involves using different measures to understand the extent of possible errors in these estimates. In the domain of predictive analytics, the error term (e_t) is a crucial quantity, signifying the margin by which forecasts (p_t) deviate from actual observed values (d_t). This error term is formally expressed as the difference between the actual and the predicted values:

$$e_t = d_t - p_t \tag{11}$$

The difference between the actual observed value and the forecasted value is referred to as the forecast error or residual. Here, e_t captures the error margin in the forecast for period t, d_t denotes the actual value in period t, and $p_t$represents the forecasted value in the same period. To assess the accuracy of multiple forecasts, advanced techniques based on this key principle are used. These techniques fall into two primary categories: the standard measurement of error margins and the relative measurement of error margins (Hanke & Wichern, 2014).

The standard measurement relies upon the dataset's categorization, thus functioning optimally when comparing forecasts of the same product. The relative measurement, conversely, possesses the attribute of adaptability, allowing for comparisons across varied products. Delving into these categories unveils four distinct measures—each with its own merits and application contexts (Hanke & Wichern, 2014).

2.8 Standard Measurement of Error Margin

2.8.1 Mean Absolute Deviation (MAD)

Mean Absolute Deviation (MAD) provides a measure of the average magnitude of errors, devoid of their directional biases. The MAD is a straightforward yet powerful tool, reflecting the typical size of the forecast errors. It is especially advantageous in its simplicity and interpretability, offering clear insights into the average error one can expect from a forecast. This metric is calculated by summing the absolute differences between the forecasted and the actual values, and then dividing by the number of observations, as denoted by the formula:

$$MAD = \frac{1}{n} \sum |F_i - A_i| \tag{12}$$

$|F_i - A_i|$ signifies the absolute error for each forecast, ensuring that both over-predictions and under-predictions are weighted equally. F_i is the forecasted value, A_i is the actual observed value, and *n* represents the total number of paired observations. The MAD score reflects the average error's absolute size, providing an clear metric of forecast reliability (Hanke & Wichern, 2014).

2.8.2 Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) adds another dimension to the evaluation, penalizing larger errors more severely. This is achieved by squaring the deviations before averaging them, thereby amplifying the influence of larger discrepancies (Hanke & Wichern, 2014). The RMSE is expressed through the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum(F_i - A_i)^2} \tag{13}$$

The squaring of the errors $(F_i - A_i)^2$ before summing ensures that larger errors have a disproportionately greater effect on the overall measure, reflecting the potential for significant outliers to skew the forecast. Calculating the square root of the average of the squared differences brings the units back to the original data's scale, making the Root Mean Square Error (RMSE) directly comparable to the initial values(Hanke & Wichern, 2014).

Together, MAD and RMSE serve as complementary metrics, with MAD offering a median level of error magnitude and RMSE highlighting the impact of outlier deviations. In the context of selective hedging strategies, the insight provided by these metrics is vital. They enable financial analysts to calibrate their models more finely, adjusting for the typical error sizes (MAD) and the presence of outliers (RMSE). Thus, ensuring that the hedging strategies are robust, responsive, and rooted in empirical evidence.

2.9 Relative Measurement of Error Margin

2.9.1 Mean Percentage Error (MPE)

Mean Percentage Error (MPE) stands out as a measure of the relative forecast error, offering insight into the proportional inaccuracies across a spectrum of predictions (Hanke & Wichern, 2014). MPE represents the average percentage deviation between the predicted and actual values, thereby providing a lens through which the overall bias of the forecasting model can be discerned. This measure is particularly useful when comparing forecasts that span different scales or units, as it normalizes the errors to a percentage basis, allowing for a coherent cross-comparison (Hanke & Wichern, 2014).

However, the MPE possesses an inherent limitation in its calculation, as it does not discriminate between overestimation and underestimation. This means that significant opposing errors could potentially cancel each other out, leading to a deceptively low MPE and the illusion of accuracy. Despite this, the MPE can still serve as a valuable diagnostic tool, revealing whether a forecasting model has a systematic tendency to overestimate or underestimate market values. A positive MPE suggests a model's consistent underestimation of actual values, whereas a negative MPE indicates consistent overestimation (Hanke & Wichern, 2014). The formulation for the MPE is given by:

$$MPE = \frac{100}{n} \frac{\Sigma(A_i - F_i)}{A_i} \tag{14}$$

A_i denotes the actual value of *i* observation, F_i represents the corresponding forecast value, and *n* stands for the number of observations over which the MPE is being calculated. By multiplying the average percentage error by 100, we translate the error into a more intuitive percentage format, which is easier to interpret and compare.

2.9.2 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) extends the concept of MPE by taking the absolute value of each individual percentage error before averaging them out. This modification addresses the shortcoming of MPE by ensuring that all errors contribute equally to the final measure, regardless of their direction. The MAPE is hence a more reliable metric of forecast accuracy, particularly in scenarios where the cost of overestimation is not equivalent to that of underestimation (Hanke & Wichern, 2014). The MAPE is computed as follows:

$$MAPE = \frac{100}{n} \Sigma \left| \frac{A_i - F_i}{A_i} \right| \tag{15}$$

In this equation, the absolute value$\left| \frac{A_i - F_i}{A_i} \right|$ensures that each error is evaluated in terms of its magnitude alone, without being offset by opposite errors. Consequently, the MAPE offers a straightforward interpretation: the lower the value, the higher the accuracy of the forecast in capturing the true market behavior (Hanke & Wichern, 2014).

2.10 Currency

Currency in the global financial market is denoted in pairs, reflecting the value of one currency relative to another. For instance, the notation NOK/USD represents the exchange rate between the Norwegian Krone (NOK) and the United States Dollar (USD). In this pair, the NOK is the base currency, and the USD is the quote currency. The exchange rate thus indicates how many U.S. dollars are needed to purchase one Norwegian Krone. This notation system is a standardized financial market convention, facilitating the clear communication of currency values in international trade and finance (Madura & Fox, 2020)

The exchange rate between two currencies, such as NOK/USD, is influenced by a multitude of factors, both economic and political. Key economic factors include inflation rates, interest rates, and the balance of trade. Typically, a country with a lower inflation rate relative to others will see an appreciation in the value of its currency. The purchasing power parity (PPP) theory suggests that currencies will equalize in purchasing power in the long run, adjusting for differences in inflation rates (Krugman et al., 2023). Interest rates, controlled by a country's central bank, affect currency value by altering investment flows. Higher interest rates offer lenders higher returns relative to other countries, thereby attracting foreign capital, which causes an appreciation of the domestic currency (Mishkin & Eakins, 2018).

Furthermore, the balance of trade, which is the difference between a country's imports and exports, can significantly impact currency value. A surplus in the balance of trade indicates more foreign currency coming in than going out, leading to an appreciation of the domestic currency. Conversely, a trade deficit can lead to depreciation (Mishkin & Eakins, 2018). Political stability and economic performance also play crucial roles. Countries perceived as politically stable with strong economic performance tend to attract more foreign investment, strengthening their domestic currency. In contrast, political turmoil or economic downturns can result in currency depreciation due to the outflow of investments (Levi, 2007).

2.10.1 Currency fluctuations

Currency fluctuations have become a cornerstone consideration for entities engaging in commodity trading and hedging on international platforms. As the global marketplace intertwines commodities and currencies, understanding the dynamics of exchange rate movements becomes crucial. For hedgers in the commodity space, it is essential to able to recognize and manage the intertwined risks of commodity price and currency fluctuations.

Exchange rates have a profound impact on commodities priced in global market. For commodities or futures denominated in USD, an appreciating dollar against another currency can lead to increased prices due to exchange rate effects.

Hedgers who operate in a currency different from the asset is inadvertently exposing themselves to currency exchange risk. For instance, if a Norwegian company, hedges against aluminum prices fall using futures contracts denominated in USD, any NOK/USD currency fluctuations can offset gains or magnify losses from the hedging strategy.

3. Data

3.1 Spot and futures prices

The data in our thesis was sourced from Macrobond and Federal Reserve Economic Data (FRED). We use historical spot prices from FRED and compare them to futures bought on London Metal Exchange (LME).

At LME futures contract operates on daily, weekly, monthly, and quarterly structures, with contracts settling the third last business day of the month. At the exchange the futures contract is settled in 25 metric tons per contract, traded in US dollars per ton and there are options for physical or cash settlements (LME, n.d.). LME utilize rolling futures contracts to create a continuous price series for historical data analysis. This method involves connecting prices from successive futures contracts, effectively creating a consistent and extended time series for market analysis by bridging the gaps between contract expiration dates (CME Group, n.d.).

We find it appropriate to use an average of the final month for each quarter to have comparable data for the analysis. This is because Reuters forecasts for aluminum prices are reported for the end for each quarter, which is March, June, September, and December. Therefore, it would be misleading to utilize the average of the whole quarter and comparing it to a forecast for these specific months.

3.1.1 Sample period

The selection of an appropriate time horizon and data frequency is crucial in empirical analysis, as these factors significantly influence the interpretation and robustness of the results. Longer time horizons can be instrumental in understanding the effectiveness of hedging strategies over extended periods, potentially covering various market cycles and volatility patterns (Ederington, 1979; Hull, 2022). This is particularly relevant for futures hedging, as the impact of factors like contango and backwardation on hedging effectiveness may vary significantly over different market conditions and time frames (Geman, 2005).

Geppert (1995) highlights a crucial aspect in futures hedging strategy analysis by noting that Ederington's (1979) approach to calculating the Minimum Variance Hedge Ratio (MVHR) requires the futures contract duration to match the data frequency. The use of non-overlapping data, as advocated by Hull (2022), theoretically enhances the precision of estimates by ensuring data independence across periods, thereby mitigating the risk of autocorrelation within the dataset. This approach is instrumental in enhancing the validity of regression analysis outcomes, particularly concerning the fit of the regression line. Our thesis adopts the use of quarterly futures contracts for hedging durations. The rationale behind this choice lies in the higher liquidity and increased data points offered by shorter-duration contracts, which are crucial for a more robust and comprehensive analysis. This approach aligns with the recommendations of Lien and Tse (2002) , who emphasize the importance of contract liquidity and data richness in enhancing the reliability and applicability of hedging strategies in dynamic market environments.

3.1.2 In-sample period and out-of-sample period

The dataset is split into two distinct periods: an in-sample window from January 2011 to December 2016 and an out-of-sample window from January 2017 to December 2022. The in-sample period serves as the estimation window, where models and strategies are developed using historical data. This phase allows for fine-tuning and parameter estimation, identifying patterns and dynamics in the data.

In contrast, the out-of-sample period functions as the testing or evaluation window, assessing the model's performance on new, unseen data. This division enables researchers to evaluate the model's robustness across various market conditions and enhances statistical power by drawing from an extended dataset spanning different economic cycles and financial events (Campbell et al., 1997).

Reuters provided forecasts for aluminum prices starting from the first quarter of 2017. With six years' worth of analytics forecasts available, we opted to use the period from Q1 2017 to Q4 2022 as our out-of-sample dataset, while the preceding six years were designated as our estimation window.

Table 1 - Descriptive statistics

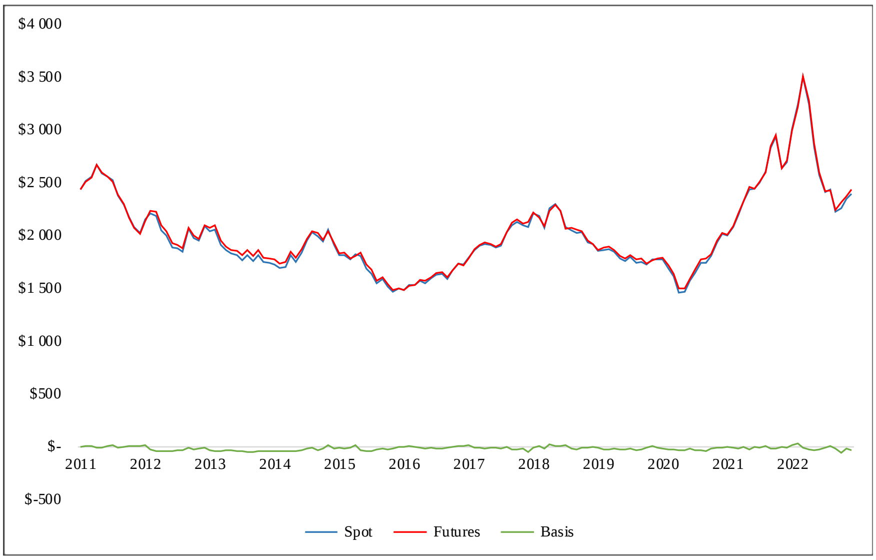
	USD		NOK	
	Spot	***Futures***	***Spot***	***Futures***
Mean	-0,0014	-0,0020	0,0107	0,0100
Standard Error	0,0143	0,0139	0,0121	0,0113
Median	-0,0080	-0,0078	0,0026	0,0047
Standard Deviation	0,0979	0,0952	0,0830	0,0777
Sample Variance	0,0096	0,0091	0,0069	0,0060
Kurtosis	1,8081	2,0887	1,2083	1,4971
Skewness	-0,2284	-0,5401	0,2654	-0,0966
Minimum	-0,3175	-0,3325	-0,2177	-0,2326
Maximum	0,2671	0,2187	0,2523	0,2040

The table shows descriptive statistics on the returns of quarterly spot and futures prices denoted in NOK and USD. The table presents the average return, volatility as variance, risk as standard deviation, distribution of data through kurtosis and skewness, minimum values, and maximum values in the dataset.

In reviewing logarithmic returns, the USD markets demonstrated negative average returns for both spot and futures instruments. Futures in USD notably showed a higher frequency of substantial negative returns, as indicated by greater negative skewness. On the other hand, the NOK markets realized positive average logarithmic returns, although with futures slightly trailing the spot market. This slight underperformance in futures is further characterized by a mild negative skewness. Standard deviations across both currencies suggest a comparable level of return volatility. The distributions, with kurtosis values below three, reveal a flatter spread than the normal distribution. These metrics indicate that during the period under study, prices in NOK saw more favorable returns, while prices in USD had negative trends.

The observed shift from negative to positive mean returns between USD and NOK can be attributed to fluctuations in the exchange rate over time, which has resulted in varying performance outcomes when measured in the respective currencies.

Figure 1 - Historical development of prices



The figure shows an overview of the spot and futures price development (with the corresponding basis) throughout the data period United States Dollars (USD). The basis in the figure illustrates the difference between the two respective prices, with a green line that lies around zero.

The graph provided illustrates the historical progression of spot vs. futures prices and basis from 2011 to 2022. There have been fluctuations as the prices started around $ 2,500 and has been as low as $ 1,500 before notably increasing to above $ 3,500 in Q1 2022. The immediate spike in prices were due to the sanctions from the U.S towards Russia after their invasion of Ukraine, leading to a drop in the supply (Reuters, 2023).

The market exhibited a contango state throughout the sample, as shown by the futures prices consistently being higher than the spot prices. Additionally, the basis, representing the difference between spot and futures prices, remained relatively flat and close to $0, indicating a stable relationship between the two prices over the years.

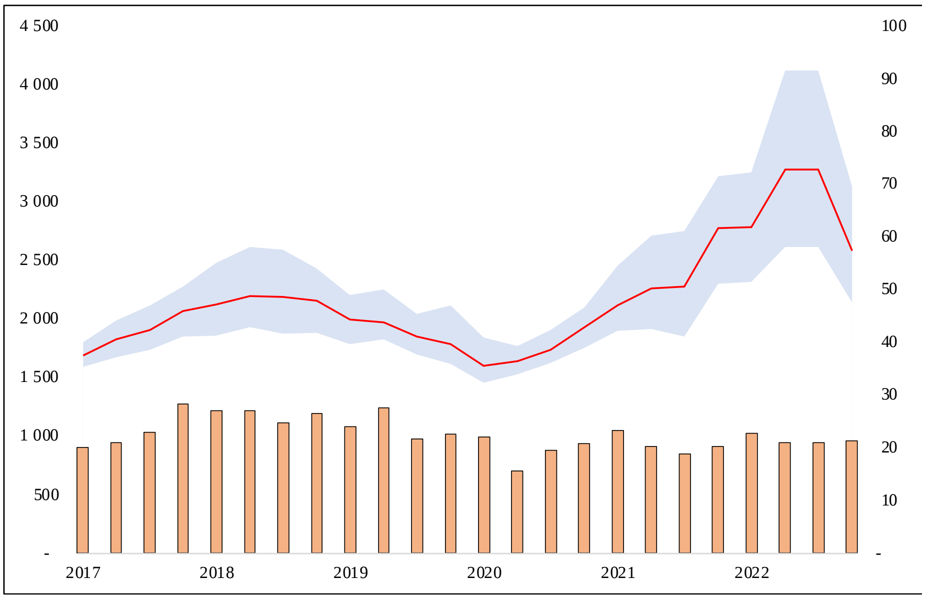
The closeness of spot and futures prices for aluminum can be attributed to several market theories. The Expectations Hypothesis suggests that futures prices are an unbiased prediction of future spot prices. If the majority of market participants expect the spot prices to be at a certain level in the future, this will be reflected in the futures prices. Additionally, the Efficient Market Hypothesis (EMH) proposes that all available information about aluminum's supply, demand, and other factors is already reflected in both spot and futures prices. Any significant discrepancies between these prices would present arbitrage opportunities, where traders could profit from the price difference. Such arbitrage activities ensure that the prices remain closely aligned (Bodie et al., 2018).

3.2 Forecasts

From the Refinitiv Eikon platform, we collected forecasts for the aluminum futures price historically. These forecasts are derived from research conducted by Reuters, offering price projections for future commodity prices. The data is collected from a diverse group of experts including economists, strategists, analysts from both buy and sell sides, independent scholars, and researchers (Reuters, n.d.).

Each forecast is an average of predictions from these contributors. The time frame for these predictions ranges from the present quarter to four quarters ahead, with additional annual predictions spanning up to two years. The number of analyses fluctuates based on the varying number of contributors submitting their forecasts every quarter. Our focus is on predictions for spot prices in the next quarter, gathering 24 observations from January 2017 to December 2022.

Figure 2 – Historical Forecasts for the Spot Price of Aluminum



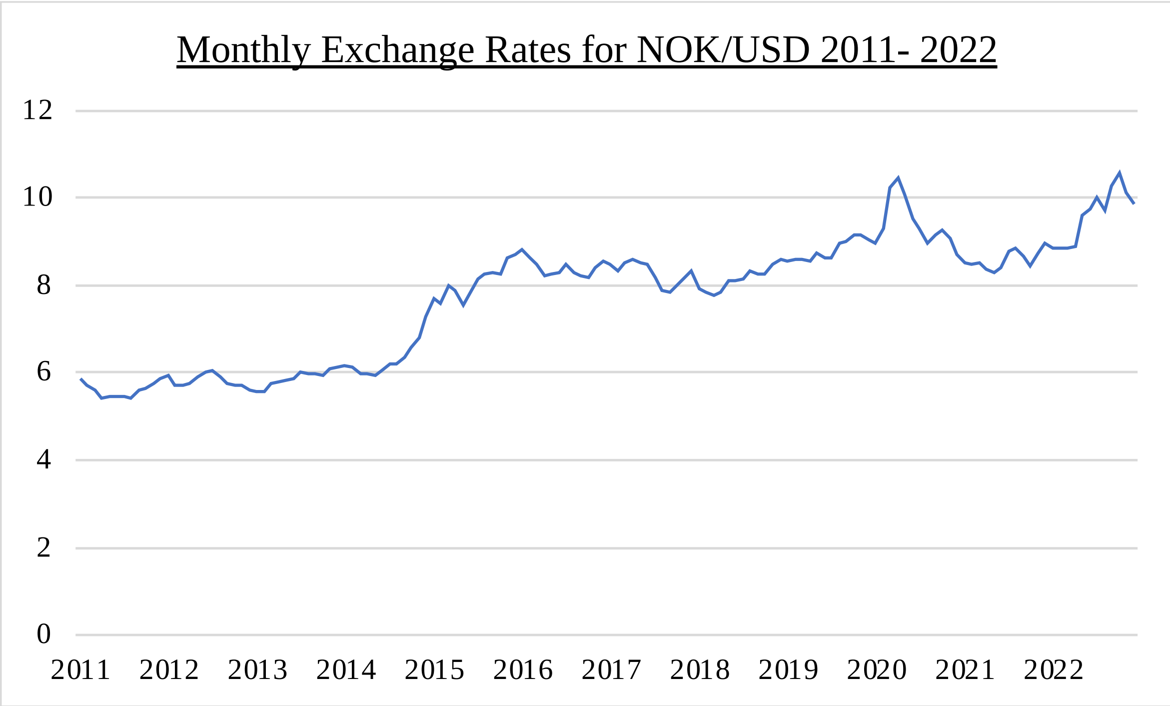
The figure displays the average predicted futures prices from qualified analysts from 2017 to 2022 (out-of-sample period). This is illustrated with the red line, where the range of estimates is shown with the blue haze. The bars on the x-axis indicate the number of forecasts that form the basis for the calculated average. The number of forecasts ranges from 20 to 30 throughout the period.

3.3 Currency exchange rates

To examine the effects of different hedging strategies on a Norwegian hedgers perspective, we use the historical exchange rates to convert the prices to a real value in NOK terms. The exchange rate information was obtained from the Central Bank of Norway. The exchange rates are middle rates, meaning they are the mean between buying and selling rates in the interbank and are determined 14.15 Norwegian time on working days (Norges Bank, 2023). For the aluminum prices, we utilize monthly averages for the final month in the quarter and have therefore obtained corresponding monthly average exchange rates.

In order for the analysis to be comparable, we have obtained exchange rates ranging from the same period, which is from January 2011 through December 2022.

Figure 3 - Monthly Exchange Rates for NOK/USD 2011-2022



This graph tracks the changes in the exchange rates between the Norwegian Krone (NOK) and the US Dollar (USD) over an eleven-year period, highlighting trends and fluctuations in currency valuation.

4. Methodology

In this chapter, we will present the methodology for calculating the Hedge Ratio (HR) for static hedging strategies and how these are adjusted by including elements from the selective hedging strategy. Subsequently, a series of statistical tests will be conducted on model parameters and the data foundation. These tests will determine the objectivity of the results and assess if the OLS-estimated values from the regression analyses qualify as the Best Linear Unbiased Estimators (BLUE).

4.1 Currency conversion

In the analysis of financial instruments such as spot and futures prices, it is critical to account for fluctuations in exchange rates that can significantly affect valuation, especially when dealing in multiple currencies. To ensure that our assessment reflects a realistic financial environment, we employ a methodology that incorporates the use of a monthly average exchange rate for the currency pair in question. This average is calculated over the entire month and applied to the quarterly price data for both spot and futures. By adopting this approach, we mitigate the effects of short-term volatility in exchange rates, thereby securing a more stable and representative rate for the month under review. This methodology not only provides a more accurate reflection of the currency's performance but also aligns with standard financial analysis practices that prioritize the use of averaged data to smooth out anomalies and provide a clearer picture of market trends over the specified period.

4.2 Estimation of hedge ratio

4.2.1 Minimum Variance Hedge Ratio

Minimum Variance Hedge Ratio (MVHR) enables the finding of Hedge Ratio (HR) by using regression analysis. We followed the approach of Johnson (1960) to find MVHR, further using regression analysis to calculating HR. This approach allows for the estimation of the HR by considering the regression coefficient as the MVHR and R^2as an indicator of hedging effectiveness.

$$r_s = \beta_0 + \theta \times r_f + \varepsilon \tag{16}$$

The return on the spot and futures prices is represented by r_s and r_f, where HR (θ) is the proportion of the investment in the futures price. The estimated coefficients for HR, R^2, t-values, p-values, and f-values for quarterly contracts in both currencies are located in the Appendix.

4.2.2 Utility-Based Hedge Ratio

When calculating the Utility-Based Hedge Ratio (UBHR) by integrating the risk aversion parameter (γ), which varies from zero to infinity, one finds the optimal balance between spot and future prices that corresponds to a given level of risk aversion. This calculation sets the stage for determining both the expected return and the variance of the HR under a spectrum of risk aversion scenarios.

As we explore the relationship between UBHR and the risk aversion parameter, we observe that the UBHR gravitates towards the MVHR as the risk aversion parameter extends to infinity. This shift is significant as it allows for the construction of a return curve. This curve is instrumental in evaluating the performance of hedging strategies retrospectively, providing insights into their efficiency across varying levels of risk aversion.

This methodology enables the construction of a hedging strategy that not only focuses on minimizing risk but also considers the investor's utility. By considering the full range of the risk aversion parameter, from non-existent to infinitely risk-averse, we can retrospectively analyze and determine the practical utility of the hedging strategies that were implemented.

$$MVHR = \lim_{\gamma \to \infty} \left(\frac{-E\ (\Delta F_{t+1})}{2\gamma Var(\Delta F_{t+1})} + \frac{Cov(\Delta S_{t+1}, \Delta F_{t+1})}{Var(\Delta F_{t+1})} \right) \tag{17}$$

4.2.3 Naive Hedge Ratio

The Naive Hedge Ratio (NHR) is a straightforward hedging strategy where the proportion of the investment allocated to the futures market is consistently set to unity (HR = 1). The computation is grounded in equation (3), which serves as the foundation for calculating the return on the hedged portfolio. This approach assumes a one-to-one hedge, where each unit of the asset is offset by an equivalent unit in the futures contract, reflecting a direct and uncomplicated relationship between the spot and futures positions. Naive Hedge Ratio (NHR) stands out for its simplicity and straightforward application.

$$r_H = \Delta S_t - 1 \times \Delta F_t \tag{18}$$

4.2.4 Forecast-Adjusted Hedge Ratio

The approach for integrating forecast adjustments into hedge ratio calculations begins with the foundational static strategies of MVHR and NHR. The pivot towards a Forecast-Adjusted Hedge Ratio (FAHR) incorporates selective strategy elements, with adjustments made based on varying market forecasts. This adjustment process is a response to expected movements in future prices, allowing the hedge ratio to evolve as the market's future trajectory is projected. For a trader with significant capital tied up in a commodity, this will mean reducing exposure in the futures market if predictions indicate an upward price trend. Conversely, they will increase their exposure if predictions indicate a downward price trend.

To calculate the FAHR, we start by establishing the Naive and MVHR as the base. The adjustment is then methodically derived by examining the divergence between the forecasted future market prices and the actual spot prices. The formula for this calculation is as follows:

$$HR_P = HR_{Naive}^{MV} \times \left(1 - \frac{Forecast - Spot}{Spot}\right) \tag{19}$$

When predicting future prices, adjusting MVHR and Naive hedge ratio depends on the variance between the forecasted and actual spot prices within the current trading cycle. How these ratios are adjusted depend on the accuracy of the forecasting model used. Within this thesis, the analytical framework involves Reuters forecasts, naive forecasting techniques, and models that integrate both trend and seasonal variations to project future price movements.

Should the forecasting models signal a contraction or expansion in future prices, there will be a corresponding increase or decrease in market hedging activities. The forecast adjusted hedge ratio changes with predictive signals, adjusting the hedge to match the scale needed for the current period. Specifically, under the naive forecast model, where the predictive component is effectively zero, adjustments to the HR are predicated on the previously observed period's returns. Subsequent sections will delve deeper into these forecasting methodologies, dissecting their respective implications on the hedge adjustment process.

4.2.5 The naive forecasting method

The naive forecasting method stands as the most elementary form of prediction, assuming that the future will mirror the immediate past. This method continually updates across a time series, serving primarily as a benchmark against which more complex forecasting techniques are measured. Its underlying assumption is the unpredictable nature of prices, which are thought to follow a random walk. Hence, the current period's price is taken as the best estimate for the next, as encapsulated by the equation:

$$\hat{Y}_{t+1} = Y_t \tag{20}$$

Where $\hat{Y}_{t+1}$ represents the forecasted price of the spot contract for the upcoming period. Y_t represents the actual observed value at time *t* (Hanke & Wichern, 2014).

4.2.6 Multiple regression

Commodities often exhibit seasonal variations. Consequently, we incorporated a forecasting method that accounts for both trend and seasonal variation. This was achieved through a multiple linear regression analysis on the quarterly spot prices, where the return (r_t) for the next period is defined by the following regression line:

$$r_t = \beta_0 + \beta_1 t + \beta_2 D_1 + \beta_3 D_2 + \beta_4 D_3 + \varepsilon_t \tag{21}$$

The regression line includes a constant term, β_0, representing the average return in the last period, and β_1, which are constant seasonal parameters. The trend component is modeled by setting t = 1, 2, ..., T, where t represents the number of data points in the estimation window. This approach captures the trend as the difference in returns between the respective period and the last period.

To predict seasonal variations, we constructed dummy variables, where $D_{n-1} = 1$ if within the specified period and $D_{n-1} = 0$ otherwise, with n being the number of periods. To avoid multicollinearity issues, the last period is represented implicitly if all other dummy variables are 0. This means that, for example, the return for fourth quarter is not explicitly included but is captured in the intercept of the regression line (β_0). For quarterly data we adjust four periods (n = 4) within a year.

4.3 Test for data validity

To validate the results, we perform a data quality analysis of the return on spot and the futures prices. Here, the basic data is tested for necessary assumptions by OLS (Ordinary Least Squares) that must be satisfied to obtain correct and effective estimates from the regression analysis. If the Gauss-Markov assumptions are satisfied, estimates are made parameters BLUE (Best Linear Unbiased Estimator), which in turn facilitates interpretation and discussion of the results. We begin by testing the basic data for stationarity and cointegration, before we move on to testing the returns for normal distribution, homoscedasticity, serial correlation, and linearity.

4.3.1 Stationarity test

The Augmented Dickey-Fuller (ADF) test is a statistical method used to determine if a time series is stationary. The Dickey-Fuller test examines the presence of a unit root in a time series, which indicates non-stationarity. In simpler terms, if a time series, like aluminum prices, has a unit root, its statistical properties like mean and variance, change over time, making analysis challenging. In the context of aluminum spot and futures prices, the ADF test is particularly useful as it accounts for potential autocorrelation that may arise from market inefficiencies (Dickey & Fuller, 1979).

The null hypothesis of this test states that the time series has a unit root, which means that it follows a random walk. If we fail to reject the null hypothesis at a significant level it implies that the series is stationary and does not have a unit root. In the other end, if we fail to reject the null hypothesis it means that the time series is non-stationary and the changes over time does not revolve around a constant mean or variance (Dickey & Fuller, 1979).

Table 2 - Stationarity test

Time series	Value	Critical value at 1% level	Critical value at 5% level	Critical value at 10% level	p-value
Exchange rate USD/NOK	-4,13***	-3,614	-2,944	-2,606	0,0009
Futures prices in NOK	-0,391	-3,607	-2,941	-2,605	0,9116
Futures prices in USD	-2,103	-3,607	-2,941	-2,605	0,2434
Return on futures in NOK	-4,022***	-3,614	-2,944	-2,606	0,0013
Return on futures in USD	-4,13***	-3,614	-2,944	-2,606	0,0009
Return on spot in NOK	-4,154***	-3,614	-2,944	-2,606	0,0008
Return on spot in USD	-4,342***	-3,614	-2,944	-2,606	0,0004
Spot prices in NOK	-0,453	-3,607	-2,941	-2,605	0,9009
Spot prices in USD	-2,124	-3,607	-2,941	-2,605	0,2348

The results from the stationarity test are displayed in this table. The exchange rates and the return series are significant at a 1% level and indicate stationarity. The null hypothesis is rejected in the price series and we can conclude that they are not stationary, which is ideal in our case.

Table 2 shows our results after conducting the ADF test on each of our time series. The null hypothesis for the USD/NOK exchange rate is rejected and we can conclude that it is stationary. This indicates that they fluctuate around a constant mean and variance over time. This can suggest that the market for this currency pair is efficient, meaning that all available information is already reflected in the exchange rate, and thus it moves randomly around its mean without a predictable trend. For traders and policymakers, this stationarity can imply that future rates are not simply a continuation of past trends but are influenced by short-term factors and can revert to the mean over time. This can have implications for hedging strategies and economic planning. The non-stationarity of the price series implies that the prices have trends or other patterns that evolve over time. This characteristic can be typical in financial markets, where prices are influenced by a multitude of factors that can cause them to drift upwards or downwards over long periods.

The stationarity in the return series suggests that the returns tend to fluctuate around a long-term mean, and their variability remains fairly constant over time. This implies that any deviations from the mean are temporary and that the returns will revert to the mean over time, which is also known as mean reversion. For the return series, stationarity is favorable because it suggests that past values and volatility do not indefinitely influence future values, allowing for more reliable statistical modeling and forecasting (Hall, 1994).

4.3.2 Cointegration test

The Engle-Granger cointegration test is a method used in time series analysis to determine whether a long-run equilibrium relationship exists between two or more non-stationary series. When individual time series themselves are non-stationary but a linear combination of them is stationary, they are said to be cointegrated. The Engle-Granger method, developed by Robert Engle and Clive Granger is divided in two steps. First, an ordinary least squares (OLS) regression is conducted on the non-stationary variables, and then the residuals from this regression are tested for stationarity using a unit root test like the Dickey-Fuller. If the residuals are found to be stationary, it indicates that despite the individual time series following a stochastic trend, they move together over time and do not drift apart, suggesting the presence of cointegration and thus a stable long-term relationship. This is particularly relevant in the study of financial markets, as cointegrated assets can provide insights into market efficiencies and opportunities for arbitrage (Engle & Granger, 1987).

Model Specification:

The long-run equilibrium relationship between spot and futures prices is modeled as follows:

$$Spot\ Price_t = \beta_0 + \beta_1 \text{ X } Futures\ Price_t + \ \varepsilon_t \tag{22}$$

First-Step Regression Results:
The OLS regression results are presented in Table 15.The estimated coefficients suggest a positive relationship between spot and futures prices. The high R-squared value of 0.9902 in the regression results signifies that futures prices can explain approximately 99% of the variation in spot prices, indicating a strong model fit.

ADF Test on Residuals:

Table 3 - Engle-Granger Test for Cointegration

Engle-Ranger Test For Cointegration	
ADF Test Z(t)	-5,348
Critical values:	
1% Level	-3,607
5% Level	-2,941
10% Level	-2,605
MacKinnon approximat p-value	0,000

Results of the Engle-Granger Test for Cointegration: The ADF Test statistic of -5.348 is well below the critical values at the 1%, 5%, and 10% levels, indicating rejection of the null hypothesis of no cointegration, with the MacKinnon approximate p-value at 0.000 confirming the significance of the result.

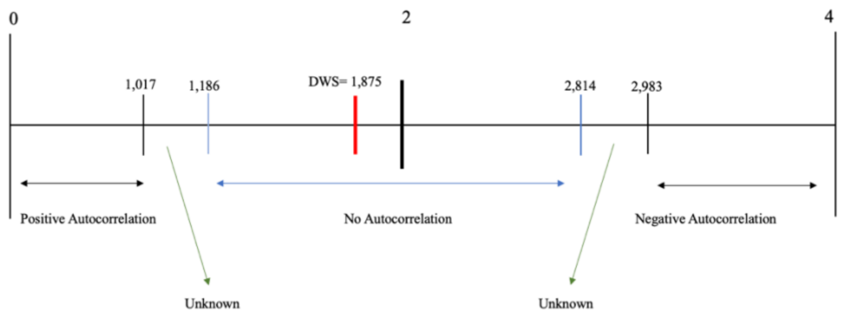
Residuals from the first-step regression Table 15 in the appendix were obtained to test for the presence of a unit root, which would indicate non-stationarity and hence no cointegration. The null hypothesis (H0) proposes the presence of a unit root in the residuals, while the alternative hypothesis (H1) suggests stationarity. The ADF test statistic is more negative than the critical values at conventional significance levels, and the p-value is less than 0.01. We therefore reject the null hypothesis, indicating that the residuals are stationary. The stationarity of the residuals suggests that there is a cointegrating relationship between spot and futures prices. This implies a stable long-term equilibrium relationship, which is a critical underpinning for effective hedging strategies in the commodities market.

4.3.3 Autocorrelation – Durbin Watson Test

The Durbin-Watson test is a statistical procedure used to detect the presence of autocorrelation in the residuals from a regression analysis. Autocorrelation is when the residuals, or the differences between observed and predicted values, are not independent of each other. Autocorrelation can violate the assumption of independent errors in a linear regression model and potentially result in biased estimates. The test gives a value that ranges from 0 to 4, where a value around 2 suggests no autocorrelation, values towards 0 indicate positive autocorrelation, and values towards 4 imply negative autocorrelation. The Durbin-Watson test is crucial because autocorrelation can invalidate some of the key assumptions of standard regression models and affect the reliability of hypothesis tests (Brooks, 2019).

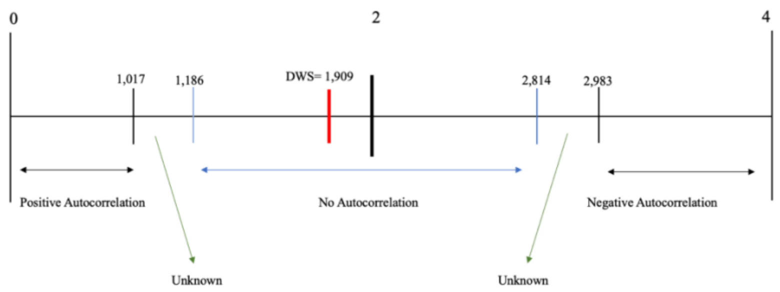
The test assesses whether a pattern exists in the error term across periods, which are expected to be independent of each other. This implies independence between period 1 and period 2. The null hypothesis of the test is that there is no significant autocorrelation in the error term, while the alternative hypothesis is that significant autocorrelation in the error term does exist. Prerequisites for the test include the error term's normal distribution and stationarity, which were confirmed by the Jarque-Bera test and the Dickey-Fuller test (Brooks, 2019).

Figure 4 - Durbin Watson test results in USD



The scale ranges from zero to four, where values around two indicate independence between periods. The lower boxes explain the significant autocorrelation that is applicable for each interval. At a 1% confidence interval, we find that DWS = 1,875 *falls within the boundaries between* 1,186 *and* 2,814*, which will prevent findings of significant results for autocorrelation.*

Figure 5 – Durbin Watson test results in NOK



The scale ranges from zero to four, where values around two indicate independence between periods. The lower boxes explain the significant autocorrelation that is applicable for each interval. At a 1% confidence interval, we find that DWS = 1,909 *falls within the boundaries between* 1,186 *and* 2,814*, which will prevent findings of significant results for autocorrelation.*

For our regression model, the Durbin-Watson d-statistic for prices in NOK is 1,909, calculated with 23 degrees of freedom. The d-statistic for prices denoted in USD is 1,875, with the same degree of freedom. From the Durbin-Watson statistics table in the appendix we can obtain the lower bounds on a 1 % significant level for 23 observations. By subtracting these values from 4 we have the parallel upper bounds for the test. The d-statistics for each regression and the respective boundaries are displayed in figure 4 and 5 above.

4.3.4 White Test – Test for heteroskedasticity

The White test is a statistical tool in regression analysis which is designed to detect heteroskedasticity. Heteroskedasticity is a condition where the variance of the error terms is not constant across observations. This test is utilized by regressing the squared residuals of the original regression model against a set of explanatory variables. These explanatory variables include the original independent variables and also their squares and cross product terms. The intuition behind this approach is to capture any systematic change in the variance of the residuals that might be related to the level or interaction of the independent variables.

Figure 6 - White Test Results for heteroskedasticity in NOK and USD

White test in NOK

H0: Homoskedasticity
Ha: Unrestricted heteroskedasticity

Chi-squared	=	**0,97**
Prob > Chi-squared	=	**0,6142**

Cameron & Trivedi's decomposition of IM-test

Source	Chi-squared	df	p
Heteroskedasticity	**0,97**	**2**	**0,6142**
Skewness	**2**	**1**	**0,157**
Kurtosis	**0,77**	**1**	**0,379**
Total	**3,75**	**4**	**0,4406**

White test in USD

H0: Homoskedasticity
Ha: Unrestricted heteroskedasticity

Chi-squared	=	**0,44**
Prob > Chi-squared	=	**0,8009**

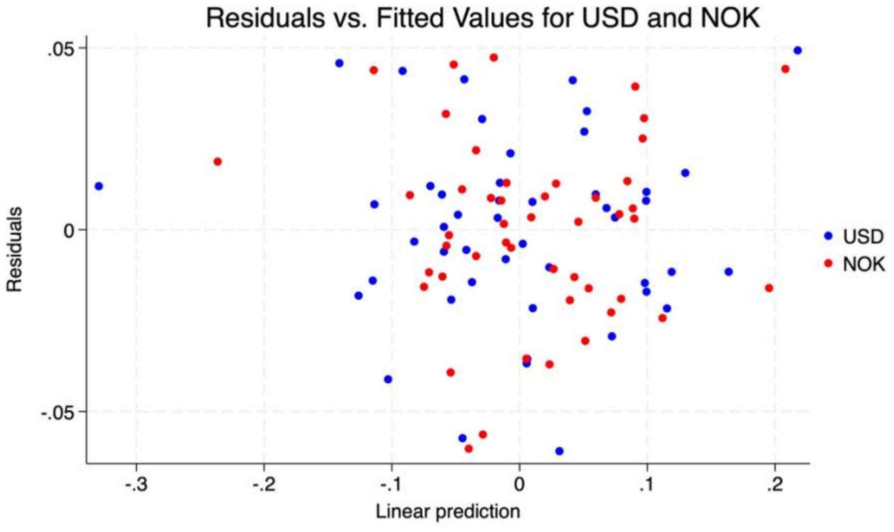
Cameron & Trivedi's decomposition of IM-test

Source	Chi-squared	df	p
Heteroskedasticity	**0,44**	**2**	**0,8009**
Skewness	**1,24**	**1**	**0,265**
Kurtosis	**0,55**	**1**	**0,4564**
Total	**2,24**	**4**	**0,6915**

The test statistics indicate a lack of evidence against homoskedasticity for both currencies, as the p-values are above common significance levels. Additionally, Cameron & Trivedi's decomposition of the IM-test shows no significant skewness or kurtosis, reinforcing the absence of heteroskedasticity in the residuals of the models.

Based on the White test results for heteroscedasticity in both NOK and USD, we can conclude that there is no evidence of heteroscedasticity in either currency. The chi-squared statistics are 0.97 for NOK and 0.44 for USD, with corresponding p-values of 0.6142 and 0.8009, respectively. Since both p-values are well above conventional significance levels (0,05), we fail to reject the null hypothesis of homoskedasticity. This suggests that the variances of the error terms are constant across the values of the independent variables in both regressions, indicating a good fit for the linear regression assumptions.

Figure 7 – Visual inspection for heteroskedasticity



This graph illustrates the residuals of linear predictions compared to the actual values for the US Dollar and Norwegian Krone, with no clear pattern emerging, suggesting a good fit for the linear model.

This scatter plot visualizes the residuals versus fitted values for the regression in NOK as well as USD. The plot provides further evidence of homoskedasticity as the points are randomly scattered and does not follow a pattern, shape, or trend. There is also no systematic change in the spread of residuals as the fitted values change.

4.3.5 Jarque-Bera test – Normality in distribution

The Jarque-Bera test is a type of statistical test that is used to check whether a given dataset has the skewness and kurtosis matching that of a normal distribution. Skewness measures the asymmetry of the probability distribution, while kurtosis measures the tailedness, which is the sharpness of the peak of a frequency-distribution curve. The test combines these two measures into a single statistic that has a chi-squared distribution with two degrees of freedom. A high p-value in the Jarque-Bera test (above 0,05), suggests that the null hypothesis of normality cannot be rejected (Brooks, 2019).

Table 4 - Jarque-Bera test results

Time series	Observations	Pr(skewness)	Pr(Kurtosis)	Joint test Adjusted Chi-squared	p-value
Return on spot in NOK	47	0,4254	0,1109	3,38	0,1847
Return on futures in NOK	47	0,7697	0,0687	3,62	0,1639
Return on spot in USD	47	0,4914	0,0417	4,64	0,0982
Return on futures in USD	47	0,1155	0,0269	6,70	0,0350

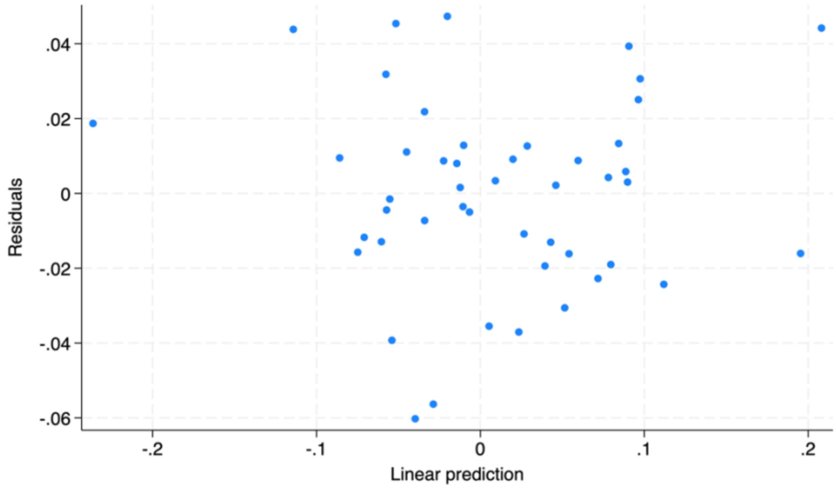
This table presents the results of the normality test with 47 observations for each time series. The skewness and kurtosis values, along with the adjusted Chi-squared and p-values, indicate that the distributions do not significantly deviate from normality, with the exception of the futures returns in USD which reaches the threshold for significance.

The Jarque-Bera test results for the returns in both NOK and USD indicate that the distribution of returns is consistent with a normal distribution with the exception of return on futures in USD. There is no statistically significant evidence to refute the hypothesis that the other returns are normally distributed as the p-values for the returns are 0,1847 and 0,1639 and 0,0982 respectively. However, the returns on futures in USD present a p-value of 0,0350, which is below the conventional threshold of 0,05. This signals that this time series might deviate from normal distribution.

The test statistics, represented by the Adjusted Chi-squared values, align with the chi-squared distribution given the degrees of freedom for each time series along with the associated p-values. These p-values, particularly for skewness and kurtosis, are high enough to suggest that the observed asymmetry and tail density in the data do not significantly differ from those of a normal distribution. This means that the skewness and kurtosis of the return distributions do not show significant abnormalities, reinforcing the non-rejection of normality in these financial time series.

4.3.6 Test for Linearity

Figure 8 - Test for linearity



This plot evaluates the linearity of the model by displaying the residuals against the predicted values. The random scatter of points suggests that the linear model assumptions may be appropriate, as there is no obvious pattern or systematic deviation visible.

The plot shows that the residuals, which represent the discrepancies between the observed values and those predicted by the model, are scattered randomly around the horizontal axis that represents zero. This pattern suggests that the assumption of linearity holds true for the data at hand, meaning the relationship between the independent variables and the dependent variable can be adequately captured by a straight line.

There is no obvious pattern indicating any systematic deviation from linearity, such as curvature or heteroscedasticity. Moreover, the absence of outliers or extreme values further strengthens the validity of the linear model. This kind of residual distribution implies that the model's predictions are unbiased, and the error variance is consistent across all levels of prediction. Both assumptions are fundamental for reliable econometrics analysis (Brooks, 2019).

4.3.7 Summary of additional test

In summary, we find statistically significant results for the normal distribution and homoscedasticity in the variance of the error term in our regression line using the Jarque-Bera test and White test, respectively. We also find no signs of autocorrelation in the error term between time periods from the Durbin-Watson test. Consequently, from the data quality analyses, it can be concluded that the estimated values from the regression analysis are BLUE (Best Linear Unbiased Estimators).

4.4 Test of data

In this study, a paired t-test was conducted to compare the mean returns of futures and spot prices in both NOK and USD. The purpose of a paired t-test is to compare the means of two related groups to determine if there is a statistically significant difference between them (Keller, 2017). In the USD dataset the mean difference between futures and spot prices is 0.0006473 with a p-value for this test was 0.8618, which is significantly higher than the conventional alpha level of 0.05. This result implies that there is no statistically significant difference in the mean returns between futures and spot prices denoted in US dollars. Similarly for the NOK dataset, the mean difference was 0.0006473 with a corresponding p-value of 0.8618, indicating a lack of statistical significance in the mean returns difference. These results suggest that for both currencies, the mean returns of futures and spot prices do not differ significantly. This supports the hypothesis that these markets may be efficiently integrated or exhibit similar risk-return characteristics within the studied period.

Figure 9 - Two-tailed paired t-test between the in-sample and out-of-sample periods in USD

t-Test: Paired Two Sample for Means		
	Return of spot in USD	*Return of futures in USD*
Mean	-0,001400243	-0,002047568
Variance	0,009585249	0,009071663
Observations	47	47
Pearson Correlation	0,965929438	
Hypothesized Mean Difference	0	
df	46	
t Stat	0,175081976	
P(T<=t) one-tail	0,430891805	
t Critical one-tail	1,678660414	
P(T<=t) two-tail	0,861783609	
t Critical two-tail	2,012895599	

The table displays the test results for the return on spot and futures contracts between the in-sample period and the out-of-sample period for USD. Since we find a p-value higher than the critical levels, we cannot reject the null hypothesis for the test, and consequently, there is no evidence of significant differences between the periods.

Figure 10 - Two-tailed paired t-test between the in-sample and out-of-sample periods in NOK

t-Test: Paired Two Sample for Means		
	Return of spot in NOK	*Return of futures in NOK*
Mean	0,010678487	0,010031162
Variance	0,006892031	0,006030508
Observations	47	47
Pearson Correlation	0,952401048	
Hypothesized Mean Difference	0	
df	46	
t Stat	0,175081976	
P(T<=t) one-tail	0,430891805	
t Critical one-tail	1,678660414	
P(T<=t) two-tail	0,861783609	
t Critical two-tail	2,012895599	

The table displays the test results for the return on spot and futures contracts between the in-sample period and the out-of-sample period for NOK. Since we find a p-value higher than the critical levels, we cannot reject the null hypothesis for the test, and consequently, there is no evidence of significant differences between the periods.

5. Results

In this chapter we will explore the results of the hedging strategies. The strategies will be measured by their effectiveness for maximizing utility and mitigating risk. Additionally, we study the accuracy of the forecasts to add a more thorough understanding of the forecast adjusted effects. Throughout the chapter the results are examined in NOK and USD separately.

The results for the different hedging strategies in each currency are summarized in Table 5. The analyses are done on the out-of-sample period where the average HR, SE, return (μ), variance (σ), standard deviation (σ), and Sharpe Ratio (μ/σ) are calculated ex post:

Table 5 – Results from the hedging strategies denoted in USD and NOK

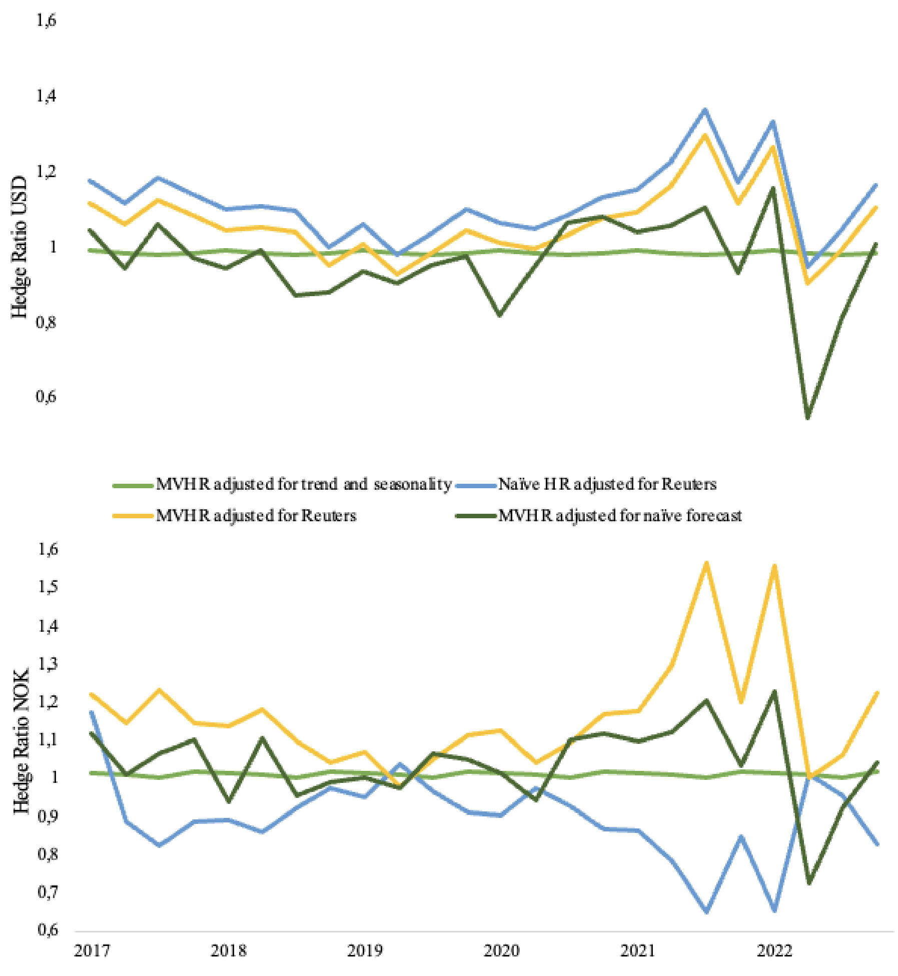
USD	HR	HE	Expected return	Variance	Std. Deviation	Sharpe Ratio
HR = 0	0	0,000	1,343%	1,412%	11,881%	11,303%
Naive HR	1	0,931	0,380%	0,068%	2,600%	14,615%
MVHR	1,021	0,933	0,051%	0,094%	3,074%	1,669%
Naïve HR adjusted for Reuters	1,119	0,922	1,033%	0,111%	3,325%	31,079%
MVHR adjusted for Reuters	1,063	0,932	0,914%	0,096%	3,094%	29,551%
MVHR adjusted for naive forecast	0,961	0,892	1,095%	0,152%	3,902%	28,059%
MVHR with seasonal and trend adjustment	1,017	0,934	0,074%	0,099%	3,139%	2,357%

NOK	HR	HE	Expected return	Variance	Std. Deviation	Sharpe Ratio
HR = 0	0	0,000	1,934%	0,984%	9,918%	19,503%
Naive HR	1	0,931	0,380%	0,068%	2,600%	14,615%
MVHR	1,029	0,905	-0,056%	0,093%	3,051%	-1,826%
Naive HR adjusted for Reuters	0,900	0,843	1,070%	0,154%	3,929%	27,233%
MVHR adjusted for Reuters	1,166	0,835	1,350%	0,162%	4,030%	33,484%
MVHR adjusted for naive forecast	1,041	0,897	0,714%	0,102%	3,190%	22,371%
MVHR with seasonal and trend adjustment	1,012	0,905	0,041%	0,093%	3,055%	1,357%

The tables provide an overview of the average hedge ratio (HR), hedging effectiveness (HE), average return (μ), volatility represented by the variance (σ^2), risk represented by the standard deviation (σ), and Sharpe Ratio (μ / σ) for each of the hedging strategies. The table displays the results for hedging strategies for USD and NOK respectively.

When looking at the results from the analysis we observe that the hedge ratios (HR) range from approximately 0,9 to above 1,1. The ratio is held constant in the portfolio HR = 0 and Naive HR. Any hedge ratio above zero involves investing a portion of the total value of the assets in the futures market while leaving the remaining share exposed to the spot market. When a hedge ratio is greater than 1, it implies that the investor is holding a position in futures contracts that exceeds the value of their underlying assets. To finance this larger position, they simultaneously sell an equivalent value of the assets in the current market. The hedge ratios for most of the portfolios are set above 1 due to the high r-squared and the higher volatility in spot prices compared to futures which is presented in Table 1. The hedge ratios for the forecast adjusted portfolios are dynamic and the value displayed in this table is the average HR. Figure 11 illustrates how the ratios has moved throughout the out-of-sample period.

Figure 11 - Development in forecast adjusted Hedge Ratio in out-of-sample period



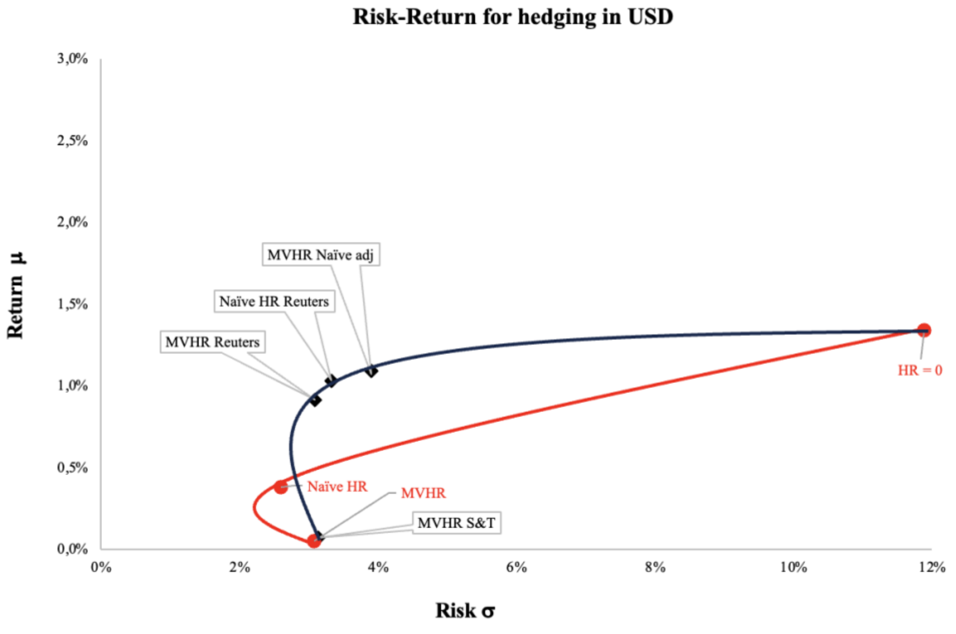
The figure shows how the static MVHR adjusted for forecasts has evolved during the out-of-sample period from 2017 - 2022. The top shows the evolvement of the hedge ratio in USD, while the bottom shows the hedge in NOK.

Figure 11 illustrates the progression of the different hedge ratios that have been modified with a forecast method. The progression of hedge ratios denoted in USD is seemingly more stable and less volatile compared to NOK. It is also evident that MVHR adjusted for trend and seasonality exhibits a consistent and stable trend with a hedge ratio around 1 throughout the years. An interesting observation is that the other hedge ratios follow a similar structure in USD, while the similarity disappears in the NOK graph. In general, we can conclude that the MVHR adjusted for trend and seasonality offers a more conservative approach, whereas the other ratios have been more volatile.

5.1 Risk-return relationship

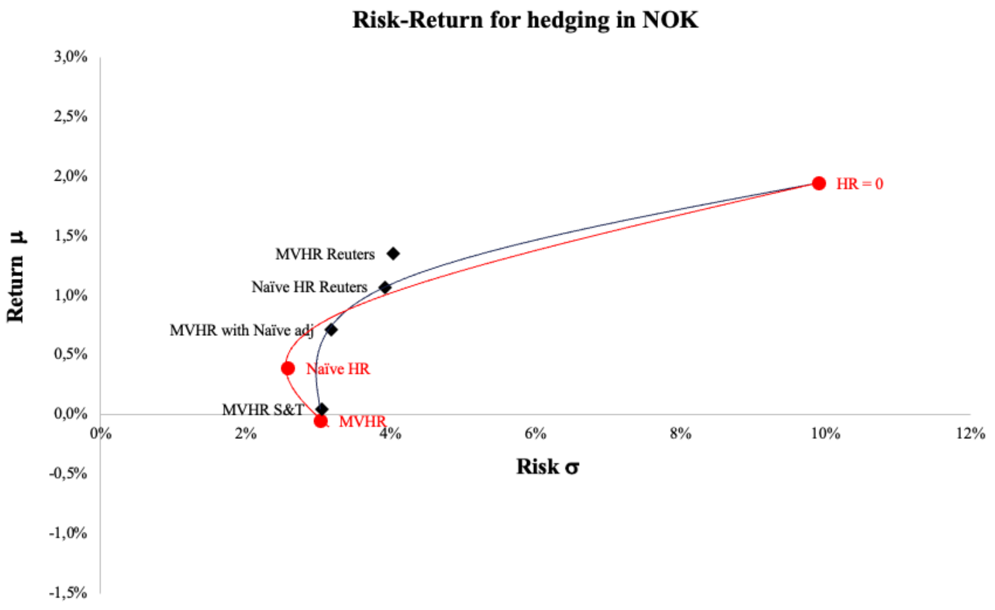
In the risk-return diagrams below, risk is displayed on the x-axis and return on the y-axis, with each of the hedging strategies represented as data points. An ideal placement would be in the top left corner of the diagram, indicating high return at low risk (Markowitz, 1991). The risk-return diagram is based on the UBHR with different risk aversion levels before and after the forecast adjustments. This results in different weightings between the spot and futures market, illustrating where in the return diagram actors will be positioned, given their risk aversion. Risk aversion ranges from zero to infinity, where an actor with infinite risk aversion would be at the Minimum Variance Hedge Ratio (MVHR). Conversely, market actors with lower risk aversion will move towards HR = 0. This creates a return curve that illustrates what actors can expect from a given hedging strategy, based on the purpose of the hedging strategy.

Figure 12 - Risk-Return for hedging in USD



The graph displays the relationship between risk and return for the hedging strategies in USD. Risk is on the x-axis and Return is on the y-axis. Where you want to place yourself on this axis depends on the purpose of the hedging strategy and the risk aversion of the trader.

Figure 13 - Risk-Return for hedging in NOK



The graph displays the relationship between risk and return for the hedging strategies in NOK. Risk is on the x-axis and Return is on the y-axis. Where you want to place yourself on this axis depends on the purpose of the hedging strategy and the risk aversion of the trader.

In the return diagrams, a red line represents strategies before forecast adjustments, while a black line denotes post-forecast selective strategies, clearly distinguishing their respective performances. In both USD and NOK analyses, MVHR and HR = 0 represents the extremes in selective strategy effectiveness, where the latter does not contribute to risk reduction. The Naive HR consistently outperforms MVHR across both currencies, achieving a higher return with lower risk exposure. This superiority could be attributed to a multitude of factors. In NOK, it might be the result of a heightened correlation between spot and futures prices or increased volatility in the out-of-sample period relative to the in-sample period. Conversely, in USD, the elevated risk could stem from volatile spot combined with a lower exposure in the futures market. It can also be due to differences in the in-sample-period compared to the out-of-sample period denoted in USD.

5.2 Results based on risk minimization

Hedging Effectiveness (HE) serves as the primary metric for assessing the success of a hedging strategy aimed at risk reduction. In the risk-return diagram, the portfolio positioned furthest to the left in the risk-return diagram is the most effective for this purpose, regardless of the expected return.

Table 6 - Ranking of the hedging strategies by risk minimization

Rank by HE	USD
1	MVHR with seasonal and trend adjustment
2	MVHR
3	MVHR adjusted for Reuters
4	Naive HR
5	Naive HR adjusted for Reuters
6	MVHR adjusted for naive forecast
7	HR = 0

Rank by HE	NOK
1	Naive HR
2	MVHR with seasonal and trend adjustment
3	MVHR
4	MVHR adjusted for naive forecast
5	Naive HR adjusted for Reuters
6	MVHR adjusted for Reuters
7	HR = 0

Ranking of the hedging strategies from best (1) to worst (7) with the goal of minimizing risk. The results are illustrated for both USD and NOK.

In the USD market, the hedging strategy rankings from Table 6 reveal a preference for more sophisticated methods when aiming to minimize risk. The top-ranked strategy is the MVHR with seasonal and trend adjustments, indicating that incorporating these specific market factors can lead to a superior risk minimization profile. The standard MVHR ranks second in effectiveness, followed by the MVHR adjusted for Reuters data. These rankings indicate that while adding news and trends can be advantageous, the specific details and complexity of the information included result in different outcomes for hedging success. Interestingly, the Naive HR strategies, whether adjusted for Reuters or not, rank lower, underscoring that simple approaches may not be as effective in the more volatile and complex USD market.

Conversely, the NOK market presents a contrasting scenario where the Naive HR stands out as the most effective strategy, as indicated by Table 6. This result challenges the notion that more complex strategies are always preferable by showcasing the efficiency of a seemingly simpler approach. At the bottom of the list, the HR = 0 strategy confirms its ineffectiveness in both currencies, aligning with the understanding that a non-hedging stance exposes the portfolio to full market volatility.

Overall, these rankings reflect that the complexity of a hedging strategy does not necessarily equate to a higher effectiveness in reducing risk. The absence of a consistent pattern across the currencies suggests that a market participant in Norway might choose a different strategy, considering that exchange rate volatility could magnify the price risk.

5.3 Results in terms of return and risk

Table 7 - Ranking of hedging strategies by Sharpe Ratio

Rank by Sharpe Ratio	USD
1	Naive HR adjusted for Reuters
2	MVHR adjusted for Reuters
3	MVHR adjusted for naive forecast
4	Naive HR
5	HR = 0
6	MVHR
7	MVHR with seasonal and trend adjustment

Rank by Sharpe Ratio	NOK
1	MVHR adjusted for Reuters
2	Naive HR adjusted for Reuters
3	MVHR adjusted for naive forecast
4	HR = 0
5	Naive HR
6	MVHR with seasonal and trend adjustment
7	MVHR

Ranking of the hedging strategies from best (1) to worst (7) with the goal of minimizing utility (relationship between risk and return). The results are illustrated for both USD and NOK.

Table 5 clearly shows that the HR = 0 strategy outperforms other hedging strategies in terms of return, with the highest returns occurring in NOK. Then again, this return diminishes when considering the Sharpe ratio, which adjusts for risk. The highest ratios are produced when the MVHR and HR are adjusted for both Reuters and naive forecasts across both currencies. For both currencies, MVHR and HR adjusted for Reuters and naive forecasts yield the highest ratio.

Table 7 displays that there is definite value in updating the portfolio balance based on the market information as these adjusted strategies outperform the static ones by clear margin. When looking at the static hedging strategies, the HR = 0 and Naive HR are outperforming the MVHR in both currencies. The lower ranking of MVHR adjusted for trend and seasonality suggests that these factors may not be as relevant or accurately captured when looking at the aluminum market.

Conclusively, our findings reveal that hedging strategies incorporating market forecasts deliver the best risk-adjusted returns. This suggests that timely, relevant information can significantly enhance a strategy's performance, as evidenced by the higher Sharpe ratios achieved through these adjustments. In contrast, strategies that do not take advantage of such information, including the HR = 0 approach, yield lower effectiveness in risk-adjusted terms. Furthermore, the underperformance of the MVHR when adjusted for seasonal and trend factors indicates that these specific adjustments may not hold as much predictive power in the context of the aluminum market.

5.4 Accuracy tests

Table 8 - Results from the accuracy tests

	USD			NOK		
Metrics	**Reuters**	**Naive forecast**	**Season adjusted**	**Reuters**	**Naive forecast**	**Season adjusted**
MAD	$ 281,58	$ 209,16	$ 89,22	NOK 2 453,79	NOK 1 584,86	NOK 787,31
RMSE	$ 399,57	$ 312,30	$ 99,77	NOK 3 489,57	NOK 2 338,52	NOK 876,32
MPE	11,40%	0,65%	-4,25%	11,40%	1,45%	-4,25%
MAPE	11,85%	8,86%	4,29%	11,85%	7,57%	4,29%

The table above shows the results from the accuracy analysis for the forecasts in both USD and NOK spot prices. The accuracy analysis is based on four metrics (MAD, RMSE, MPE, and MAPE) that are assessed for each of the hedging strategies for both currencies.

The Reuters expert predictions have a relatively high MAD and RMSE values in both currencies, indicating a larger average error and a higher average of the squared errors, respectively. This suggests that the forecasts are less precise. The MPE at 11.40% for both USD and NOK shows that the forecasts tend to underestimate. Despite this, the MAPE values are consistent at 11.85%, signifying that on average, the forecast errors amount to this percentage of the actual values, whether over or underestimating.

Naive forecasts, which assume that the future price will mirror the most recent price, show lower MAD and RMSE values. This implies a closer proximity to the actual prices and suggests a better prediction performance than the Reuters method. The MPE values tell a contrasting story between the two currencies. A MPE value close to zero in USD indicates almost no bias on average, while the MPE in NOK suggests a slight tendency to underestimate. The MAPE is lower compared to Reuters, especially in NOK, which implies a smaller average error relative to the actual values.

While other methods display consistency between currencies, the naive forecast method reveals a different pattern. MPE and MAPE do not remain equivalent when transitioning from USD to NOK. This discrepancy is attributed to the methodological approach employed in the naive forecast model. This is due to an exchange rate lag, where the previous period's exchange rate is used in the naive forecast model. To achieve better alignment between the two currencies, one could apply the subsequent month's exchange rate to adjust a naive forecast, when reviewing in hindsight. However, in a present context, this method is not feasible for future forecasts. This is due to the upcoming period's exchange rate being unknown, preventing currency conversion at the current time.

Seasonally adjusted forecasts display the lowest MAD and RMSE values among the three methods in both USD and NOK, suggesting these are the most accurate predictions. The negative MPE in both currencies indicates a consistent overestimation bias. MAPE is the same for both currencies at 4.29%, indicating that the magnitude of errors is the smallest on average, despite the direction of the bias.

5.4.1 Precision of forecast considering the hedging strategies ranked

By examining the results from Table 6 and

Table 7 we cannot see an obvious coherence between the forecast accuracy and hedging strategy ranking. Reuters' forecasts perform poorly in accuracy compared to other forecasts. However, when measuring Sharpe ratio, the strategies adjusted for Reuters are performing better. The superior Sharpe Ratio associated with these strategies may indeed be a function of the additional risk introduced by less accurate forecasts, which can inadvertently lead to capturing sporadic profitable opportunities in volatile market conditions.

Another insight is the consistency between seasonally adjusted forecasts and hedging effectiveness. These forecasts are the most accurate and yields the highest HE. It is intuitive as the HE is calculated by measuring the variance of the portfolio compared to the variance of the spot price. The forecasts suggest a hedge ratio that is close to 1 and which results in higher hedging effectiveness and indicates strong protective measures against market variations.

5.4.2 Currency repercussions

When comparing the accuracy in USD versus NOK, the MAD and RMSE are substantially higher in NOK across all methods, which could be due to the added variability from exchange rate fluctuations. Interestingly, the MPE is consistent for Reuters across both currencies, while the naive and seasonally adjusted methods show less bias in USD than in NOK. This might suggest that currency fluctuations have a more pronounced effect on simpler forecasting models. The MAPE values are relatively stable across currencies for each method, suggesting that the proportional size of the errors remains similar despite the currency conversion.

While the absolute errors (MAD and RMSE) are higher in NOK than in USD, this does not necessarily reflect a greater inaccuracy in forecasts due to the higher nominal values in NOK. The stable MAPE values underscore that the relative errors remain comparable across currencies. Therefore, it is crucial to consider both absolute and relative error metrics when analyzing currency repercussions to gain a complete understanding of the predictive models` accuracy.

5.5 Hedging Strategies for Norwegian Entities

For a Norwegian entity operating in the aluminum market, the interplay of hedging strategies between the Norwegian Krone and the US Dollar is a critical financial decision influenced by currency volatility and risk-return dynamics. The analysis presented reveals that hedging strategies that are effective in USD do not necessarily translate seamlessly to NOK, largely due to differences in currency volatility and market behavior.

In the context of NOK, the Naive Hedge Ratio (HR) strategy emerges as particularly effective, suggesting a simpler approach may yield better results in a market characterized by less predictability and higher volatility. This contrasts with the USD market, MVHR with seasonal and trend adjustments seem to offer superior risk minimization. This implies that the more complex and information influenced strategies that cater to the nuances of the USD market might be excessive for NOK hedging needs.

The Sharpe Ratio results indicate that strategies adjusted for Reuters forecasts enhance hedging performance across both NOK and USD, offering a universal benefit in terms of risk-adjusted returns. This suggests that irrespective of the currency, incorporating expert financial forecasts into hedging strategies tends to provide an advantage, possibly by allowing entities to anticipate and capitalize on market movements more effectively.

In conclusion, for Norwegian entities, the choice of hedging strategy in NOK should be informed by the unique behavior of the local currency, which exhibits different volatility and market dynamics compared to USD. A balanced approach that considers both the simplicity of naive forecasts and the potential benefits of more sophisticated strategies could be key to optimizing hedging performance in the face of currency risks.

6. Discussion

In this chapter, we will explore the potential added value of forecast-adjusting hedging strategies for participants in the aluminum market with operations in Norway where the focus will be on the tradeoff between risk and return. Initially, we examine the influence of forecast accuracy, then proceed to evaluate the performance of different hedging strategies. Further, there will be done a significance test based on our results. Finally, we aim to inspect whether the results from forecast-adjusted hedging strategies are based on chance or skill by testing the stability of the results. This will determine whether if forecast-adjusted hedging strategies yields significantly better results than hedging strategies. Throughout the whole discussion, the focus will be on how the Norwegian supplier is affected.

6.1 Forecasts and hedge ratio

The combination of static and selective hedging strategy gives the trader a continuous hedging relationship, which makes it possible to deviate from the return curve of the static hedging strategies. A forecast adjustment of the hedge ratio makes it possible to manage the exposure to the spot and futures market in accordance with the market view. This makes it possible for traders to achieve a higher return relative to price risk for the commodity by increasing (reducing) the exposure in the futures market if the forecasts indicate and decrease (increase) in the futures prices. The disadvantage of continuous exposure to the futures market, which is also the price to pay for the reduced risk, is the opportunity cost in situations where the participant does not receive full returns from a rising or falling spot price. To succeed with forecast adjustments, and reap the benefits of reduced price risk, one is dependent on forecasts with good estimates of future prices. However, failed forecasts will contribute to reduced risk since one is still exposed to the futures market with forecast-adjusted hedging strategies.

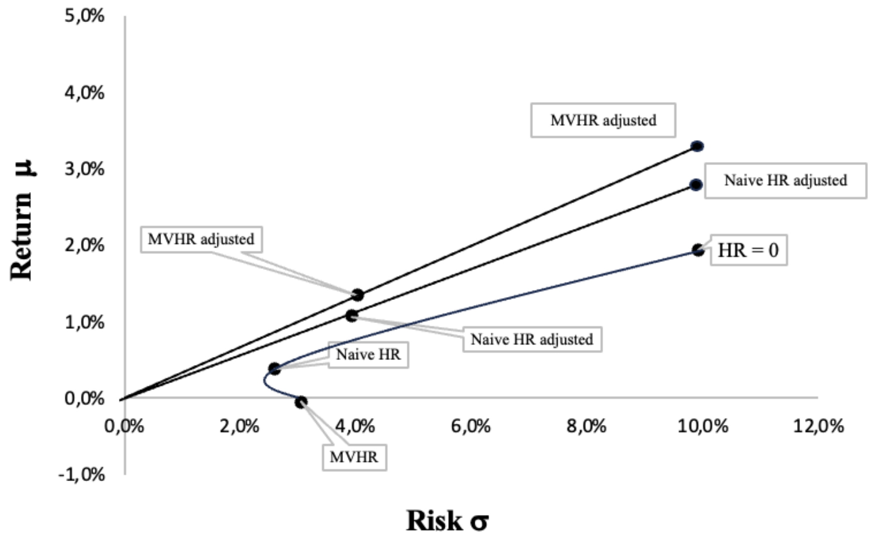
The effectiveness of forecasting in financial markets significantly depends on the quality of forecasting tools and their adaptability to changing market trends. This principle is exemplified in the analysis of Reuters forecasts, which incorporate macroeconomic indicators, historical prices, and general outlooks for the aluminum market. Despite scoring lower in accuracy tests, Reuters forecasts interestingly rank highest in terms of the Sharpe ratio. This divergence suggests that absolute accuracy in forecasting is not always essential for creating a profitable portfolio. Portfolios based on Reuters forecasts, even with their lesser accuracy, achieve positive returns combined with lower risk, thus meeting the objective of Sharpe ratio. The weak relationship between forecast precision and portfolio success underscores the multifaceted nature of market forecasting.

In comparison, the MVHR adjusted for seasonality and trends stands out for its high accuracy. This method shows the least deviation from actual prices, which is exhibited in Table 8. However, when examining the relationship between forecast accuracy and hedging effectiveness (HE), it becomes more complex. In terms of NOK, the seasonally adjusted MVHR leads in HE, followed by the naive forecast and then Reuters. Conversely, in USD terms, the seasonal adjustment yields the highest HE, closely followed by the Reuters adjustments and the naive approach. This inconsistency in our data highlights that there is no clear, direct pattern between the accuracy of forecasts and their impact on HE, alluding to the nuanced dynamics of forecast application in commodity hedging.

6.2 Optimal hedge ratio

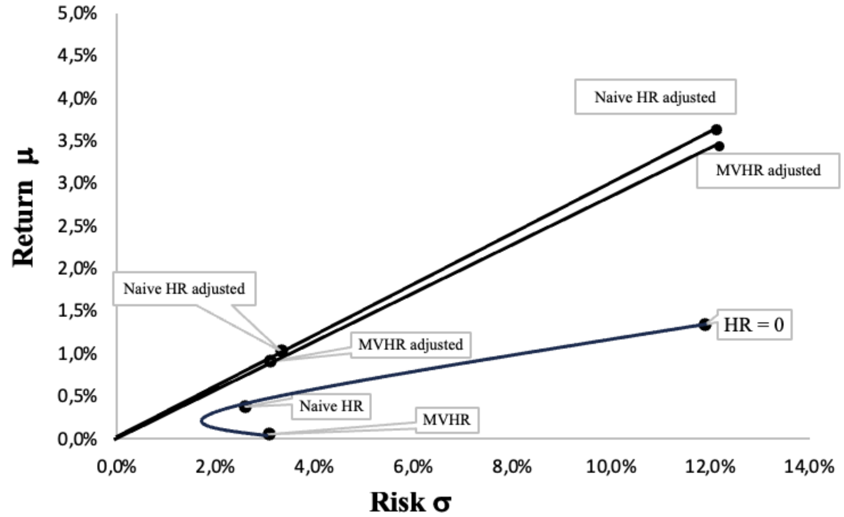
The highest Sharpe ratio among static hedging strategies in both NOK and USD is the HR = 0. After the Reuters forecast adjustments, we clearly observe that it is possible to increase this excess return per unit of risk. Figure 12 and Figure 13 illustrates this by displaying with new positions of the MVHR and Naive HR in both currencies.

Figure 14 - Illustration of the added value by adjusting for Reuters in NOK



The figure displays the relationship between return and risk for hedging strategies in USD. Risk is on the X-axis and average return is on the y-axis. The illustration focuses on how the straight line from the origin shifts inward in the diagram when adjusted for Reuters, resulting in a higher Sharpe Ratio for moth MVHR and Naive HR when taking as much risk as the HR = 0

Figure 15 - Illustration of the added value by adjusting for Reuters in USD



The figure displays the relationship between return and risk for hedging strategies in NOK. Risk is on the X-axis and average return is on the y-axis. The illustration focuses on how the straight line from the origin shifts inward in the diagram when adjusted for Reuters, resulting in a higher Sharpe Ratio for moth MVHR and Naive HR when taking as much risk as the HR = 0

The figures above confirm that MVHR and Naive HR adjusted for Reuters yield higher returns with comparable risk as the HR = 0 portfolio. This implies that a trader will achieve a higher return by adjusting for Reuters if the risk aversion parameter equals to zero. In theory, this would be optimal, but in reality, it requires selling large volumes in the underlying assets and futures market to match these results. Despite seeming unrealistic, it demonstrates that adjusting hedging strategies to include Reuters Forecasts can lead to better returns. However, adjusting for forecasts does increase the price risk, which is unwanted when conducting risk-minimizing strategies. To analyze the effect of forecast adjustment and the risk one incurs with increased returns, the difference between HE and Sharpe Ratio is calculated. This is presented in Table 9 below.

6.3 Forecast adjusted added value

Table 9 - Forecast adjusted added value

	USD		NOK	
	Hedging Effectiveness	**Sharpe Ratio**	**Hedging Effectiveness**	**Sharpe Ratio**
Naïve HR	0	0	0	0
Naïve HR adjusted for Reuters	-1,0%	16,5%	-8,8%	12,6%
MVHR	0	0	0	0
MVHR adjusted for Reuters	-0,1%	27,9%	-7,0%	18,9%
MVHR adjusted for naive forecast	-4,1%	26,4%	-0,9%	7,8%
MVHR with seasonal and trend adjustment	0,1%	-1,3%	0,0%	-13,3%

The risk-return ratio that the trader is left with by changing the objective from reducing price risk to maximizing utility, illustrated by adjusting Naive HR and MVHR for forecast. The results are displayed in both USD and NOK.

The table displays the impact of incorporating forecast adjustments into the two static strategies: Naive HR and MVHR. We examine the changes in the HE and Sharpe ratio for each strategy. The Naive HR adjusted for Reuters shows an improvement in the risk-adjusted returns for both USD and NOK, but it loses its hedging effectiveness. The same sentiment pertains to the MVHR and its adjustments for forecasts, with the exemption of seasonality and trend adjustment. When the MVHR is adjusted for seasonality and trend, it moves oppositely. We observe that the HE increases or stays the same, while the Sharpe ratio decreases.

Our findings imply that for a static hedging strategy to gain more risk-adjusted return, it has to increase the risk level, which is reflected in a lower hedging effectiveness in the adjusted strategies. This is consistent with our findings in chapter 5 where we observed that the less accurate forecasts deliver the best Sharpe ratios. The seasonal and trend adjusted forecasts is more accurate and thus less risky.

6.4 Test for significance

Further, we conduct an analysis of the effectiveness of hedging strategies by determining if adjustments for forecasts can lead to statistically significant improvements in risk-adjusted returns. By testing the null hypothesis that there is no difference between the Sharpe ratios of forecast-adjusted and non-adjusted strategies, we seek to identify whether the inclusion of market information plays a significant role in hedging performance.

Table 10 - Test for significance in Sharpe ratio

USD	Sharpe Ratio	Std Deviation
Naïve HR adj for Reuters	0,31	0,0333
Naive HR	0,15	0,026
Difference	0,16	
Correlation	0,20	
SE	0,00	
Z score	149,59	
P-value	0,00	

NOK	Sharpe Ratio	Std Deviation
MVHR adj for Reuters	0,33	0,04
Naive HR	0,15	0,03
Difference	0,19	
Correlation	0,34	
SE	0,001	
Z score	174,58	
P-value	0,00	

The table presents the results from a significance test comparing hedging strategies in USD and NOK. It shows the Sharpe Ratio, standard deviation, and Z-scores, highlighting statistically significant differences between strategies adjusted for Reuters forecasts and non-adjusted benchmarks across both currencies.

The statistical analysis of hedging strategies using the Sharpe ratio reveals significant differences in risk-adjusted returns. In USD, the Naive HR adjusted for Reuters significantly outperforms the Naive HR benchmark, indicated by a Z-score of 149,59 and a p-value of 0,00. A similar pattern is observed in NOK, where MVHR adjusted for Reuters also yields a higher Sharpe ratio than Naive HR, with a Z-score of 174,58 and a p-value of 0,00. These results strongly suggest that incorporating Reuters forecast adjustments into hedging strategies greatly enhances their performance compared to not hedging.

With a p-value of 0,00, you can reject the null hypothesis that there is no difference between the Sharpe ratios of the strategies being compared. The high Z-scores confirm that the differences in Sharpe ratios are not only statistically significant but also practically significant, given their magnitude. This implies that the strategies adjusted for Reuters information provide a substantially better risk-adjusted return compared to a strategy with a one-to-one hedging strategy, in both currencies. The consistency across both currencies underscores the robustness of forecast-adjusted strategies over the unadjusted benchmark.

A p-value of essentially zero indicates an extremely low probability that the observed differences in Sharpe ratios could have occurred by chance. This result is typically driven by a substantial disparity between the compared strategies' performance metrics, such as a large difference in Sharpe ratios coupled with a small standard error, which collectively suggest a high level of statistical significance in the observed data.

6.5 Stability in hedging results and market events

The paired two-sample t-test applied in this analysis is utilized to compare Sharpe ratios of hedging strategies in the aluminum market from the first to the second half of the study period. The null hypothesis assumes no significant difference between the Sharpe ratios of the two periods, implying consistent performance from 2017 through 2022.

Table 11 - Paired two-sample t-test

t-Test: Paired Two Sample for Means	**USD**	
	Variable 1	*Variable 2*
Mean	0,07319347	0,26788143
Variance	0,00530102	0,05491917
Observations	7	7
Pearson Correlation	0,5922303	
Hypothesized Mean Difference	0	
df	6	
t Stat	-2,5751458	
P(T<=t) one-tail	0,02102149	
t Critical one-tail	1,94318028	
P(T<=t) two-tail	0,04204297	
t Critical two-tail	2,44691185	

t-Test: Paired Two Sample for Means	**NOK**	
	Variable 1	*Variable 2*
Mean	0,06460253	0,23401429
Variance	0,00388036	0,05171989
Observations	7	7
Pearson Correlation	0,61455255	
Hypothesized Mean Difference	0	
df	6	
t Stat	-2,2936592	
P(T<=t) one-tail	0,03081699	
t Critical one-tail	1,94318028	
P(T<=t) two-tail	0,06163397	
t Critical two-tail	2,44691185	

The table displays the test results for Sharpe Ratio on the seven hedging strategies between the first and second period in our out-of-sample dataset.

For the USD, the test produces a t-statistic of -2,575 with a two-tail p-value of 0,042. Given that this p-value is slightly less than the standard alpha level of 0,05, it indicates a statistically significant difference, suggesting that the performance of the hedging strategy varied between the two halves of the analysis period. Conversely, the NOK results reveal a t-statistic of -2,294 and a two-tail p-value of 0,061, which does not meet the threshold for statistical significance. This outcome suggests that the hedging strategy's performance in terms of the Sharpe ratio did not significantly fluctuate over time, pointing to stability.

The disparity in Sharpe ratios between the periods can be influenced by a variety of factors, including currency fluctuations, market volatility, and significant economic events. Currency movements can have an effect on hedging strategies with exchange rate volatility potentially altering the risk-return when converted into the trader’s home currency. Market volatility, driven by changes in supply and demand within the commodity markets, can directly impact the returns of hedging strategies.

Moreover, extraordinary economic events such as the COVID-19 or the invasion of Ukraine lead to extreme volatility. During the COVID-19 pandemic, global markets faced extreme volatility. The initial outbreak caused a precipitous drop in demand for many commodities (Tan et al., 2022).. This resulted in a sharp decline in prices for commodities like oil and aluminum, affecting the returns of related hedging strategies. As the pandemic progressed and economies started to adapt, some commodities experienced a rapid increase in demand, leading to price surges. This results into high volatility component of Sharpe ratios. Russia's invasion of Ukraine in 2022 had immediate effects on commodity markets. Sanctions imposed on Russia, a major producer of commodities like oil and natural gas, led to supply fears, causing prices to spike. This increased cost had a knock-on effect on a wide range of industries, including aluminum, where Russia is also a key supplier (International Agricultural Trade Report, 2022).

7. Conclusion

In volatile markets it is paramount to succeed with hedging strategies and reap the benefits of reduced price risk. In these markets traders are deeply dependent on forecasts with good estimates of future prices. Further, the effectiveness of forecasting in financial markets significantly depends on the quality of forecasting tools and their adaptability to changing market trends. In this thesis we have investigated how various hedging strategies have performed in managing the volatility in the aluminum market, additionally from the perspective of a Norwegian entity. Throughout this thesis we have investigated and compared various hedging approaches, assessing their effectiveness in navigating market uncertainties. The Norwegian perspective has been incorporated to provide an understanding of how the integration of a currency element influences the effectiveness of these strategies.

The purpose of this thesis has been to find out which strategy has performed best in terms of risk minimization and utility maximization. We have conducted analysis on quarterly prices in USD and NOK from 2017 through 2022, while using the preceding six years as an estimation window. To enhance our analysis, we have also conducted statistical tests to ensure the quality of the data and results.

7.1 Analyses and results

Our main goal with this thesis has been to find out if there is any added value to adjusting static hedging strategies with forecasts. We chose the perspective of a Norwegian aluminum producer who not only faces risk through volatility in commodity prices, but also currency risk. Throughout our sampling period, Reuters forecast adjusted strategies has yielded the highest Sharpe ratio for both currencies. The MVHR and Naive HR both adjusted for Reuters, stood out as clear winners in USD and NOK. This implies that in terms of utility maximization, adjusting a static hedge ratio for Reuters forecasts is optimal. When studying hedging effectiveness, it is not as clear if a selective adjustment gives added value. Portfolios with static and selective strategies rank 1st and 2nd place in both currencies, indicating that forecast adjusting does not definitively translate to lower risk. The MVHR and MVHR adjusted for seasonality and trend rank among the highest in both currencies, indicating that the portfolio deriving from these strategies yields the lowest risk. This is coherent with our assumptions as the purpose of these strategies are to reduce the variance.

Aluminum participants based in Norway are subject to exchange rate fluctuations, and we find that the most effective hedging strategies for the US Dollar may differ from those for the Norwegian Krone. Hedging strategies in NOK must consider the currency's sensitivity to market conditions, where our findings suggest that less intricate methods can outperform those that are forecast adjusted.

We have conducted multiple tests to ensure the quality of our data and results. Chapter 4.2 provides evidence that the data obtained is BLUE. We have also done a paired two-sample t-test to check for stability in our results within the out-of-sample period. The test results establishes that there has been a difference between the two periods before and after the first quarter in 2020. This aligns with our own beliefs as the period after 2020 has been influenced by high volatility through a global pandemic and the invasion of Ukraine. Additionally, we conducted a significance test of the Sharpe Ratios, were we identified whether the inclusion of market information played a significant role in hedging performance. The results indicate an extremely low probability that the observed differences in Sharpe ratios could have occurred by chance.

7.2 Limitations

Our regression analysis is based on one explanatory variable in the estimation of MVHR, which is the spot price of aluminum. There are certainly other factors that affect futures prices, which a more informative regression analysis would be able to reduce the measurement errors associated with omitted variables. Additionally, a concern is the length of our data sample. Reuters’ forecasts for aluminum prices did not reach further back than 2017, which limited our sample period from 2011 until 2022. Furthermore, this period is possibly not representative for market movements moving forward, as there has been rapid changes since 2020. The frequency of the data is also up for critique as the Reuters forecast are only announced in quarterly prices and the futures contracts can also be bought monthly. We have also only chosen futures contracts and the forward market is a viable option for an actor to hedge for price volatility.

We have chosen a simplistic approach when addressing currency risk, as we only have converted the prices for aluminum with the respective exchange rates. In the real world, traders face transaction costs, and it also possible to hedge against currency risk, which we have excluded. We also have excluded the margin requirement. The futures contract for aluminum operate on a daily mark-to-market and traders are required to provide margins at the end of trading days. Nevertheless, our study indicates that there is added value to forecast adjusting static strategies and the currency risk needs to be considered. While our study has provided a foundational analysis, it opens the door for more comprehensive research within the field.

7.3 Further research

Building upon the findings of our research, further investigation into hedging strategies within the aluminum market should prioritize several key areas. Expanding the geographic scope to include emerging markets is essential, as these regions often experience greater currency volatility, providing a more comprehensive understanding of how hedging strategies perform under different economic conditions. A long-term study across various economic cycles would shed light on the resilience and sustainability of these strategies over time.

Incorporating advanced forecasting techniques, such as machine learning and AI, could significantly enhance the accuracy of predictions, leading to more effective risk management. Comparative analysis with other commodities would reveal whether strategies effective in the aluminum market are transferable to other markets. Importantly, future studies should also consider the impact of transaction costs on hedging effectiveness, offering a more realistic assessment of the strategies' net benefits. These areas collectively promise a more nuanced and practical understanding of hedging strategies in the context of a dynamic global economy.

8. Appendix

Table 12 - Regression results for futures contracts in USD

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,966572138
R Square	0,934261698
Adjusted R Square	0,931273593
Standard Error	0,030736831
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,303336586	0,303336586	312,6603001	1,71909E-14
Residual	22	0,021343947	0,000970179		
Total	23	0,324680533			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	3,54961E-05	0,006402982	0,005543676	0,995626772	-0,013243476	0,013314468	-0,013243476	0,013314468
ret_futures_usd	1,020874893	0,055712085	17,68220292	1,71909E-14	0,869572606	1,100652193	0,869572606	1,100652193

Table 13 - Regression results for futures contracts in NOK

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,951548435
R Square	0,905444424
Adjusted R Square	0,901146443
Standard Error	0,030514
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,204866413	0,204866413	210,6673989	9,50718E-13
Residual	22	0,021394203	0,000972464		
Total	23	0,226260616			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-0,000356811	0,006508588	-0,054821567	0,956775432	-0,013854796	0,013141174	-0,013854796	0,013141174
ret_futures_nok	1,028659404	0,069567531	14,51438593	9,50718E-13	0,865455763	1,154004221	0,865455763	1,154004221

Table 14 - Durbin Watson table

Durbin-Watson Statistic: 1 Per Cent Significance Points of dL and dU

	k'*=1		k'=2		k'=3		k'=4		k'=5		k'=6		k'=7		k'=8		k'=9		k'=10	
n	dL	dU	dL	dU	dL	dU	dL	dU	dL	dU	dL	dU	dL	dU	dL	dU	dL	dU	dL	dU
6	0.390	1.142	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
7	0.435	1.036	0.294	1.676	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
8	0.497	1.003	0.345	1.489	0.229	2.102	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
9	0.554	0.998	0.408	1.389	0.279	1.875	0.183	2.433	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
10	0.604	1.001	0.466	1.333	0.340	1.733	0.230	2.193	0.150	2.690	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
11	0.653	1.010	0.519	1.297	0.396	1.640	0.286	2.030	0.193	2.453	0.124	2.892	-----	-----	-----	-----	-----	-----	-----	-----
12	0.697	1.023	0.569	1.274	0.449	1.575	0.339	1.913	0.244	2.280	0.164	2.665	0.105	3.053	-----	-----	-----	-----	-----	-----
13	0.738	1.038	0.616	1.261	0.499	1.526	0.391	1.826	0.294	2.150	0.211	2.490	0.140	2.838	0.090	3.182	-----	-----	-----	-----
14	0.776	1.054	0.660	1.254	0.547	1.490	0.441	1.757	0.343	2.049	0.257	2.354	0.183	2.667	0.122	2.981	0.078	3.287	-----	-----
15	0.811	1.070	0.700	1.252	0.591	1.465	0.487	1.705	0.390	1.967	0.303	2.244	0.226	2.530	0.161	2.817	0.107	3.101	0.068	3.374
16	0.844	1.086	0.738	1.253	0.633	1.447	0.532	1.664	0.437	1.901	0.349	2.153	0.269	2.416	0.200	2.681	0.142	2.944	0.094	3.201
17	0.873	1.102	0.773	1.255	0.672	1.432	0.574	1.631	0.481	1.847	0.393	2.078	0.313	2.319	0.241	2.566	0.179	2.811	0.127	3.053
18	0.902	1.118	0.805	1.259	0.708	1.422	0.614	1.604	0.522	1.803	0.435	2.015	0.355	2.238	0.282	2.467	0.216	2.697	0.160	2.925
19	0.928	1.133	0.835	1.264	0.742	1.416	0.650	1.583	0.561	1.767	0.476	1.963	0.396	2.169	0.322	2.381	0.255	2.597	0.196	2.813
20	0.952	1.147	0.862	1.270	0.774	1.410	0.684	1.567	0.598	1.736	0.515	1.918	0.436	2.110	0.362	2.308	0.294	2.510	0.232	2.174
21	0.975	1.161	0.889	1.276	0.803	1.408	0.718	1.554	0.634	1.712	0.552	1.881	0.474	2.059	0.400	2.244	0.331	2.434	0.268	2.625
22	0.997	1.174	0.915	1.284	0.832	1.407	0.748	1.543	0.666	1.691	0.587	1.849	0.510	2.015	0.437	2.188	0.368	2.367	0.304	2.548
23	1.017	1.186	0.938	1.290	0.858	1.407	0.777	1.535	0.699	1.674	0.620	1.821	0.545	1.977	0.473	2.140	0.404	2.308	0.340	2.479
24	1.037	1.199	0.959	1.298	0.881	1.407	0.805	1.527	0.728	1.659	0.652	1.797	0.578	1.944	0.507	2.097	0.439	2.255	0.375	2.417
25	1.055	1.210	0.981	1.305	0.906	1.408	0.832	1.521	0.756	1.645	0.682	1.776	0.610	1.915	0.540	2.059	0.473	2.209	0.409	2.362
26	1.072	1.222	1.000	1.311	0.928	1.410	0.855	1.517	0.782	1.635	0.711	1.759	0.640	1.889	0.572	2.026	0.505	2.168	0.441	2.313
27	1.088	1.232	1.019	1.318	0.948	1.413	0.878	1.514	0.808	1.625	0.738	1.743	0.669	1.867	0.602	1.997	0.536	2.131	0.473	2.269
28	1.104	1.244	1.036	1.325	0.969	1.414	0.901	1.512	0.832	1.618	0.764	1.729	0.696	1.847	0.630	1.970	0.566	2.098	0.504	2.229
29	1.119	1.254	1.053	1.332	0.988	1.418	0.921	1.511	0.855	1.611	0.788	1.718	0.723	1.830	0.658	1.947	0.595	2.068	0.533	2.193
30	1.134	1.264	1.070	1.339	1.006	1.421	0.941	1.510	0.877	1.606	0.812	1.707	0.748	1.814	0.684	1.925	0.622	2.041	0.562	2.160
31	1.147	1.274	1.085	1.345	1.022	1.425	0.960	1.509	0.897	1.601	0.834	1.698	0.772	1.800	0.710	1.906	0.649	2.017	0.589	2.131
32	1.160	1.283	1.100	1.351	1.039	1.428	0.978	1.509	0.917	1.597	0.856	1.690	0.794	1.788	0.734	1.889	0.674	1.995	0.615	2.104
33	1.171	1.291	1.114	1.358	1.055	1.432	0.995	1.510	0.935	1.594	0.876	1.683	0.816	1.776	0.757	1.874	0.698	1.975	0.641	2.080
34	1.184	1.298	1.128	1.364	1.070	1.436	1.012	1.511	0.954	1.591	0.896	1.677	0.837	1.766	0.779	1.860	0.722	1.957	0.665	2.057
35	1.195	1.307	1.141	1.370	1.085	1.439	1.028	1.512	0.971	1.589	0.914	1.671	0.857	1.757	0.800	1.847	0.744	1.940	0.689	2.037
36	1.205	1.315	1.153	1.376	1.098	1.442	1.043	1.513	0.987	1.587	0.932	1.666	0.877	1.749	0.821	1.836	0.766	1.925	0.711	2.018
37	1.217	1.322	1.164	1.383	1.112	1.446	1.058	1.514	1.004	1.585	0.950	1.662	0.895	1.742	0.841	1.825	0.787	1.911	0.733	2.001
38	1.227	1.330	1.176	1.388	1.124	1.449	1.072	1.515	1.019	1.584	0.966	1.658	0.913	1.735	0.860	1.816	0.807	1.899	0.754	1.985
39	1.237	1.337	1.187	1.392	1.137	1.452	1.085	1.517	1.033	1.583	0.982	1.655	0.930	1.729	0.878	1.807	0.826	1.887	0.774	1.970
40	1.246	1.344	1.197	1.398	1.149	1.456	1.098	1.518	1.047	1.583	0.997	1.652	0.946	1.724	0.895	1.799	0.844	1.876	0.749	1.956
45	1.288	1.376	1.245	1.424	1.201	1.474	1.156	1.528	1.111	1.583	1.065	1.643	1.019	1.704	0.974	1.768	0.927	1.834	0.881	1.902
50	1.324	1.403	1.285	1.445	1.245	1.491	1.206	1.537	1.164	1.587	1.123	1.639	1.081	1.692	1.039	1.748	0.997	1.805	0.955	1.864
55	1.356	1.428	1.320	1.466	1.284	1.505	1.246	1.548	1.209	1.592	1.172	1.638	1.134	1.685	1.095	1.734	1.057	1.785	1.018	1.837
60	1.382	1.449	1.351	1.484	1.317	1.520	1.283	1.559	1.248	1.598	1.214	1.639	1.179	1.682	1.144	1.726	1.108	1.771	1.072	1.817
65	1.407	1.467	1.377	1.500	1.346	1.534	1.314	1.568	1.283	1.604	1.251	1.642	1.218	1.680	1.186	1.720	1.153	1.761	1.120	1.802
70	1.429	1.485	1.400	1.514	1.372	1.546	1.343	1.577	1.313	1.611	1.283	1.645	1.253	1.680	1.223	1.716	1.192	1.754	1.162	1.792
75	1.448	1.501	1.422	1.529	1.395	1.557	1.368	1.586	1.340	1.617	1.313	1.649	1.284	1.682	1.256	1.714	1.227	1.748	1.199	1.783
80	1.465	1.514	1.440	1.541	1.416	1.568	1.390	1.595	1.364	1.624	1.338	1.653	1.312	1.683	1.285	1.714	1.259	1.745	1.232	1.777
85	1.481	1.529	1.458	1.553	1.434	1.577	1.411	1.603	1.386	1.630	1.362	1.657	1.337	1.685	1.312	1.714	1.287	1.743	1.262	1.773
90	1.496	1.541	1.474	1.563	1.452	1.587	1.429	1.611	1.406	1.636	1.383	1.661	1.360	1.687	1.336	1.714	1.312	1.741	1.288	1.769
95	1.510	1.552	1.489	1.573	1.468	1.596	1.446	1.618	1.425	1.641	1.403	1.666	1.381	1.690	1.358	1.715	1.336	1.741	1.313	1.767
100	1.522	1.562	1.502	1.582	1.482	1.604	1.461	1.625	1.441	1.647	1.421	1.670	1.400	1.693	1.378	1.717	1.357	1.741	1.335	1.765
150	1.611	1.637	1.598	1.651	1.584	1.665	1.571	1.679	1.557	1.693	1.543	1.708	1.530	1.722	1.515	1.737	1.501	1.752	1.486	1.767
200	1.664	1.684	1.653	1.693	1.643	1.704	1.633	1.715	1.623	1.725	1.613	1.735	1.603	1.746	1.592	1.757	1.582	1.768	1.571	1.779

*k' is the number of regressors excluding the intercept

Durbin-Watson Statistics with a 1% significance level for upper and lower bounds(University of Notre Dame, 2014).
**k' is the number of explanatory variables in the regression line, excluding the constant term.*

Table 15 - OLS Regression Results

Source	SS	df	MS			
				Number of obs	=	**48**
				F(1, 46)	=	**4653,42**
Model	**7222033,3**	**1**	**7222033,3**	Porb > F	=	**0**
Residual	**71391,2**	**46**	**1551,9**	R-squared	=	**0,9902**
				Adj R-squared	=	**0,9900**
Total	**7293424,5**		**155179,2**	Root MSE	=	**39,395**

Spot Price	Coefficient	Std. Error	t	P>|t|	[95% conf. interval]	
Futures Price	**1,007072**	**0,014763**	**68,22**	**0**	**0,9773554**	**1,036788**
Constant	**-28,05465**	**30,41737**	**0,92**	**0,361**	**-89,28165**	**33,17235**

This table presents the OLS regression results, indicating a positive correlation between spot and futures prices with a high R-squared value, signifying a significant explanatory power for spot price variability.

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