NORGES HANDELSHØYSKOLE

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HEDGING REVENUES WITH WEATHER DERIVATIVES

A literature review of weather derivatives

&

A case study of Ringnes AS

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“Everybody talks about the weather but nobody does anything about it” Mark Twain

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ABSTRACT

The corporate world has hedged their revenues for decades. By use of futures, forwards, options and swaps companies have hedged risks related to stock investments, commodities, interest rates, currency and relevant indexes. A common feature for those types of risk is that the risks are mainly related to price. Volumetric risk on the other hand, has largely been left unhedged. A common and important factor to volumetric risk is the weather. Previously adverse weather has often been used as an excuse for poor financial performance, and such excuses have to a large extent been accepted by the market. In the late 90's a new financial market was developed. A market for weather derivatives, so that risk managers could hedge their exposure to weather risk. After a slow start the weather derivatives market have started to grow rapidly. Risk managers can no longer blame poor financial results on the weather. Weather risk can be removed by hedging.

This thesis will explain briefly what a derivative is and point out some motives for use of derivatives. Thereafter we will look at the history of the weather risk market, how the weather risk market has developed in recent years and also who the current and potential players in the weather risk market are. The most famous methods for valuation of weather derivatives will also be introduced and discussed. Finally problems and possibilities of the weather derivative market will be briefly discussed.

After the general part about weather derivatives a case study will be conducted on the Norwegian brewery Ringnes AS. First several regressions are run to model the relation between beverage sales and temperature. Next the chosen model is used to decide the relation for a given period of time. After the relation between sales and temperatures is analysed, appropriate hedging strategies are discussed. Some chosen hedging strategies will be evaluated by use of common weather derivative valuation methods. Finally these analyses form the foundation for a conclusion whether or not Ringnes AS should implement weather derivatives in their risk management strategy.

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1 DERIVATIVES

1.1 General

A derivative is defined as a financial instrument that has a value determined by the price of something else (McDonald, 2006). What McDonald describes as something else is more commonly called the underlying asset. Before expiry other factors like time to expiry, volatility of the underlying and expected development contributes to determine the value of a derivative. A derivative has an expiration date T where the derivative ceases to exist. At that point a derivatives value is entirely determined by the underlying.

The value of a derivative at expiry is determined by the price of an underlying, which can be categorized into five groups; stocks, commodities, interest rates, currencies and indexes. Historically weather did not fit into any of these groups of underlying assets. By creating indexes on the weather, this problem was circumvented and some valuation techniques can now be applied to weather derivatives. While the different categories of underlying assets vary in nature, a derivative on a stock is very similar to a derivative on corn. The main difference is the nature of the underlying.

Effective hedging requires a clear understanding of the relation between the hedged position and the hedging instrument. The strength and direction of the linear relation between two variables may be measured with the use of covariance and correlation statistics. Later the concept of linear regression and several other regression models will be introduced to estimate the value of one variable from the value of another variable.

1.2 Motives for using derivatives

1.2.1 Speculation

Derivatives can be bought as an investment. If the derivative is not related to your core business, or if the derivative increases your income risk you are not hedging, you are speculating. A popular feature in derivatives for this purpose is the possibility to gear investments.

1.2.2 Arbitrage

If a derivative has an underlying which is tradable, the derivative can be replicated. Differences in derivative price and price of replicating the derivative imply that one of the assets is mispriced. With knowledge of a mispriced asset one can buy cheap and sell expensive. Such an investment will secure a guaranteed positive return. This is called arbitrage.

1.2.3 Reduced transaction costs

A financial transaction can in some cases be accomplished more cheaply by use of derivatives (McDonald, 2006). It may for example be cheaper to buy a call option on a stock than to buy a combination of stocks and bonds.

1.2.4 Hedging

A derivative is a tool with the ability to reduce risk. Most derivatives come at a price. In periods with no payoff on the hedging strategy, the corporation would be better off not using derivatives. However, in periods with poor financial performance, derivatives can be the direct reason to why corporations manage to continue their business. Therefore, in the long run benefits from derivatives are often considered to be greater than the costs. Widespread use of derivatives for hedging is a proof of this.

2 HEDGING

2.1 Reasons to hedge

Miller and Modigliani claim that corporate hedging does not alter firm value. However, they emphasize that all assumptions in their model need to hold for this to be true. Miller and Modigliani's assumptions include the absence of taxes, financial distress costs, contracting costs, information costs, and capital market imperfections (Modigliani & Miller, 1958). As soon as one of these assumptions does not hold, there is a need for corporate hedging.

In an article on corporate hedging Myers and Smith suggest seven possible reasons why corporations should hedge their assets even though their shareholders are well diversified. The article focus on use of insurance on property and liabilities, but some of their points are also valid for use of derivatives on revenues.

Stakeholders like employees, customers and suppliers can in most cases not diversify their business with the corporation. Consequently these stakeholders will require better terms with a risky corporation, as stakeholders can't diversify the corporations risk on their own (Myers & Smith, 1982).

A risky firm will also have a higher chance of going bankrupt. Use of derivatives can reduce volatility in both revenue and income. This will in turn reduce the chance of going bankrupt. Cost of borrowing depends among other on bankruptcy costs. As the chance of going bankrupt is reduced, so is the cost of borrowing. (Myers & Smith, 1982)

Progressive taxes motivate corporations to smooth their profits as smooth profits then are taxed at a lower rate than a combination of high profits followed by low profits. In addition, some tax regimes have a time-limit on losses carried forward. After a large loss, if the corporation does not generate sufficient profits to deduct prior losses within the time-limit, prior losses are no longer tax deductible (Myers & Smith, 1982). Proper use of derivatives will smooth profits, and reduce the chance of not being able to use losses carried forward.

2.2 Reasons not to hedge

The reasons to hedge are many and proper use of derivatives can increase the risk-reward relation for a company. Nevertheless, hedging comes at a cost and McDonald points out several reasons not to hedge (McDonald, 2006).

Derivative contracts can range from simple transactions as for example agreeing on a fixed price to more advanced derivatives like exotic options. The company needs to assess costs and benefits of their hedging strategy. To assess costs and benefits it is crucial that the company has expertise that understands the derivatives they are trading. Such expertise may come at a high cost through for example highly educated employers or expensive consulting firms.

Derivatives have implications also after they are traded. Transactions need to be monitored to evaluate how the hedge is performing. In addition derivative transactions have tax and accounting consequences. In particular, derivative transactions may complicate financial reporting. This might be both time-consuming and costly.

Finally, derivative transactions are not free. For each transaction there are transactions cost. In addition each transaction also has a bid-ask spread. The bid-ask spread often requires the buyer to pay more than the fair value of the derivative for the transaction to come through.

2.3 Empirical evidence on hedging

From the previous two Sections we have seen that there are reasons to hedge and reasons not to hedge. To find out which side of the argument that have strongest support from the financial market we turn to empirical evidence.

A study from 1998 showed that roughly half of US non-financial firms reported use of derivatives, and that derivatives were more commonly used among large firms (Bodnar & Marston, 1998). More interestingly, a study of companies worldwide show that companies which use derivatives have a higher market value (Allayanis, Lel, & Miller, 2007). Another study also shows that firms which hedge on average have a higher leverage (Graham & Rogers, 2001). Firms are allowed to be highly levered if they are not very risky, which would be the case if the firm hedged some of its business risk.

Based on empirical findings it seems sensible to conclude that the reasons to hedge weigh more heavily than the reasons not to hedge. Still, we cannot conclude that every company should hedge their risk. The decision to hedge is a matter of costs versus benefits. Therefore, we conclude that every company should analyse the cost of hedging their business versus the benefits of hedging their business.

2.4 Basis risk

Payoff on a derivative depends on the derivatives underlying. If an asset and the underlying of a derivative are perfectly correlated there is no basis risk. Basis risk arises as soon as an asset and the underlying asset of a derivative are not perfectly correlated. This imperfect correlation between the asset and the underlying asset of the derivative creates potential for excess gains or losses in a hedging strategy. Imperfect correlation reduces efficiency of the hedging instrument and increases risk of the total portfolio.

For weather derivatives basis risk is smallest when financial performance is highly correlated with the weather and when contracts based on optimal locations are used for hedging. For a company analysing how to hedge its weather risk there is often a trade-off between basis risk and the price of the weather hedge. Frequently traded weather contracts on metropolises like Chicago, New York and London are priced low relative to illiquid weather contracts on smaller locations. However, the majority of businesses are not located nearby the mentioned metropolises and only in few cases will contracts on the weather in metropolises minimise basis risk for the hedger. As a consequence risk managers have the choice between choosing the best locations for the hedge and minimise basis risk, or create a less accurate hedge on a location with relative cheap weather contracts. Even though relative cheap contracts may be tempting, they are not very useful if they don't correlate sufficiently with a company's business. Thus, a decision to choose cheap contracts instead of minimizing basis risk should be made with high caution.

2.5 Modelling a hedged portfolio

Section 2.1 stated reasons why derivatives should be used to hedge revenues. This chapter will review the basic mathematical principles behind portfolios, diversification and hedging as explained by (Jewson, Brix, & Ziehmann, Modelling Portfolios, 2005b).

We start by looking at the equations for mean and variance of two random variables, where γ is the weight of each asset in the portfolio. An asset can for example be a business' cash flow from operations, an investment in non-core business or a hedging instrument.

$$\mu_{A+B} = \mu_A + \mu_B \tag{2.1}$$

$$\sigma_{A+B}^2 = \sigma_A^2 + \sigma_B^2 + 2\rho_{AB}\sigma_A\sigma_B \tag{2.2}$$

The above equations can be rearranged to emphasise the changes in a portfolio of one contract, A, when another contract, B, is added.

$$\Delta\mu = \mu_{A+B} - \mu_A \tag{2.3}$$

$$\Delta\sigma^2 = \sigma_{A+B}^2 - \sigma_A^2 = \sigma_B^2 + 2\rho_{AB}\sigma_A\sigma_B \tag{2.4}$$

The equations show that when we add a second asset to the portfolio, the return μ change by the return of asset B. The risk, measured by σ^2 however, changes through two terms. The first term show that risk of the portfolio, σ_{A+B}, increase by risk of the second asset, σ_B. In addition, the second term covers interaction between asset A and asset B. This term can be both positive and negative, depending on the correlation between the two assets. The term $2\rho_{AB}\sigma_A\sigma_B$ is also called covariance. Covariance is what makes it possible to create a hedge portfolio with even lower risk than a diversified portfolio.

Comparison of the two terms reveals how a second asset will affect portfolio risk. If the variance of asset B is greater than covariance of the two assets, the portfolio risk will increase. However, if covariance is negative with an absolute value greater than the variance of asset B, portfolio risk will decrease. Equation 3.2 shows that negative covariance only is possible when asset A and B are negatively correlated.

For portfolios consisting of more than two assets we have the following equations, where N_A is the number of assets.

$$\mu_{Total} = \sum_{i=1}^{N_A} \mu_i \tag{2.5}$$

$$\sigma_{Total=}^2 \sum_{i=1}^{N_A} \sum_{j=1}^{N_A} c_{ij} \tag{2.6}$$

$$= \sum_{i=1}^{N_A} \sum_{j=1}^{N_A} \rho_{ij} \sigma_i \sigma_j$$

$$= \sum_{i=1}^{N_A} \sum_{j \neq 1}^{N_A} \rho_{ij} \sigma_i \sigma_j + \sum_{i=i}^{N_A} \sigma_i^2$$

To summarize, total portfolio risk depends heavily of the interactions between assets. Total portfolio return on the other hand, does not depend on interactions between assets. These features of portfolio risk and return can in the best cases make it possible to increase portfolio return and at the same time reduce portfolio risk.

3 WEATHER RISK

Weather risk is a general term to describe the financial exposure a business may have to weather events such as heat, cold, snow, rain or wind. (ElementRe, 2002a) Weather risk is in general non-catastrophic and the impact is more related to profitability than property, which is the case with catastrophic weather events.

A large share of the world's economy is weather sensitive, and a study from 2008 showed that $5.8 trillion of the world's economy was weather sensitive. (Weatherbill Inc., 2008) Out of these $5.8 trillion the US economy was estimated to account for $2.5 trillion. By this estimate, 23% of the US economy is weather sensitive. Another article from 2008 states that as much as one third, approximately $4 trillion, of the US economy is weather sensitive (Myers R. , 2008), while the US Department of Commerce, William Daley, in 1999 stated that at least one trillion dollars of the nine trillion dollars US economy is weather sensitive. (West, 2000) Regardless of which estimate is correct, it is obvious that both the global and the US economy is far too weather sensitive to ignore weather risk.

The range of businesses exposed to weather risk is wide. The simplest case of a vendor exposed to weather risk would be a vendor selling umbrellas. He sells a lot of umbrellas on rainy days, but no so many umbrellas on sunny days. The vendor could hedge the weather risk by also selling sunglasses.

For a small vendor exposure to weather risk can in some cases be eliminated as easy as described above. For large corporations on the other hand, hedging weather risk might be much more complex. In annual reports, worse than expected earnings are often claimed to be a result of adverse weather conditions. A quick glance at the beverage producer Carlsberg's annual report for 2008 shows the following; "Growth in the Eastern Europe also decelerated in the second half of the year as the expected recovery in the Russian beer market failed to materialise, initially due to extremely poor weather…" (Carlsberg Group, 2009). A glance at the fertilizer producer Yara's annual report for 2007 shows a similar comment; "Adverse weather conditions affected fertilizer consumption negatively, and the strongest surge in crop prices took place during the second half of the year." (Yara, 2008). Using adverse weather conditions as a scapegoat for poor financial performance have been convenient for companies since it used to be commonly accepted that weather was a factor even risk managers couldn't hedge against. The existence of a weather derivatives market might alter this, since weather risk now can be hedged just as foreign exchange risk and interest risk can be hedged.

3.1 Origins of the weather derivatives market

The following description of how the weather derivatives market originated is largely inspired by Randall's paper on weather, finance and meteorology (Randalls, 2004).

The first transaction in the weather derivative market took place in July 1996, when Aquila Energy agreed to sell electrical power to Consolidated Edison for the month of August at a fixed price, but subject to potential rebates (ElementRe, 2002a). If August month was 10% cooler than on average, Consolidated Edison would receive a rebate of $16,000, and the cooler August month was the higher rebate Consolidated Edison would receive. Weather, or more specifically weather data, had for the first time been commodified as a financial product that could be bought and sold. The first weather derivative trade took place, and was possible, due to several events in the energy and insurance industries that occurred in the 1990s.

First of all, a systematic change occurred in the 1990s as the capital and insurance markets converged. Until then capital markets and insurance were two different markets. The two markets were now starting to overlap, particularly in alternative risk transfer markets, as companies sought to use the capital markets for insurance and be less dependent on insurance products. In addition insurers often had capacity constraint on how much risk they could bear. When this limit was reached, insurers were forced to increase their buffer of capital to ensure all their risks were covered by a sufficient amount. This buffer of capital tended to be inefficient use of capital. To reduce use of such buffers, some insurers transferred risk through capital markets issues or derivative transactions tied to their insurance events. This contributed to drawing the capital markets and insurance markets closer together (ElementRe, 2002e).

Secondly, the insurance industry was experiencing a cyclical period of low premiums in traditional underwriting business. Low premiums enabled the insurance industry to provide sufficient amounts of risk capital to hedge weather risk (Considine, 2004). Insurance companies' ability to write a large base of options provided liquidity for development of a weather derivatives market.

Thirdly, electricity sector deregulation programs were undertaken in England and Wales in 1990, while the Energy Policy Act of 1992 removed important barriers for the unregulated energy and utility sectors in the US (Griffin & Puller, 2005). With the political main focus being on electricity retail price reductions and creation of opportunities for hungry new entrants, deregulation of the US energy and utility markets continued in the mid-1990s. New companies, and new business lines within traditional companies, emerged as a result of the deregulation. Emerged companies and business lines in turn resulted in increased competition among the participants in the electricity market. Especially energy resellers came to realize that while they could hedge away price risk with futures and options on energy itself, they were still exposed to adverse weather. Adverse weather could mainly affect energy resellers in two ways. One scenario was a colder than normal summer. A cold summer would reduce demand for cooling, and in turn reduce demand for energy. Reduced demand would in the end result in lower revenues for energy resellers. The second scenario, which energy resellers probably feared the most, was an extremely hot summer spiking demand for cooling and energy. Energy resellers could find themselves forced into buying additional power from the deregulated spot market where prices fluctuates with demand. In most cases, resellers couldn't pass the increased cost of energy on to customers, leaving energy resellers highly exposed to fluctuations in energy demand. What the energy and utility sectors needed was not just a hedge against prices, but also a hedge against the volume of energy required by their customers. Since customers demand to energy were highly correlated to the weather, the energy and utility sectors actually needed a hedge against the weather.

Fourthly, energy companies were eager to examine new ways to mitigate risk. The most important player was Enron. Enron promoted innovation and performed constant investigation of risks within its own business. In 1996 Enron investigated revenue fluctuations from the gas pipeline sector, and found that a warm winter substantially reduced gas sales. This was a risk to Enron, and it was decided that the risk of a warm winter needed to be managed pro-actively. A group in Enron generated an idea of a financial tool built around an index well known to energy companies, more specific, an index of degree-days. Since weather is measured independently, this index was easy to create. Under the assumption that people have different opinions to which way the index will move, that is, will it be colder or warmer, a market was in principle possible.

At first the insurance companies were reluctant to enter this market, so Enron decided to act as a risk provider to start the market. In 1997 the first major deal took place between the three US energy companies Enron, Aquila and Koch (ElementRe, 2002a). The deal created sufficient publicity to weather derivatives, this publicity made the first insurance companies enter into the weather derivatives market, resulting in more players and higher liquidity in the weather derivatives market.

Fifthly, El Niño, a warm oscillation, appeared in 1997 (ElementRe, 2002b). El Niño led to a much warmer than usual winter in the US, especially in the heavily populated North East region. Many energy companies are dependent on sales of gas and electricity in this heavily populated region. The warmer than usual winter reduced demand for gas and electricity, and substantially cut back energy companies profits.

Sixthly, advanced derivatives were becoming common in the financial market; hence a new type of derivatives would be more welcome now than ten years ago. In addition, global debates on air pollution and global climate change made businesses focus on how their earnings were affected by weather. Many businesses came to realize that their earnings could be severely impacted by adverse weather, making them potential end-users of weather derivatives.

These factors, convergence of insurance and capital markets, low insurance premiums, deregulation of electricity markets, risk management in energy companies, El Niño and the increasing awareness of the global climate changes all called for a financial tool enabling risk managers to hedge against weather. The answer to these calls was weather derivatives.

4 HOW OTHER RISK TOOLS ATTEMPT TO MANAGE WEATHER RISK

Weather derivatives are fairly new in the world of financial instruments. Still, firms have used several methods in attempts to manage their exposure to weather risk. While some of these tools are convenient tools in risk management, they should not be confused with weather derivatives. In a report on weather derivatives Myers explains how the respective tools differ from weather derivatives (Myers R. , 2008).

4.1 Diversification

Companies that rely heavily on a certain type of weather, like rain throughout the year, could seek protection by diversifying their product line with products that are not sensitive to rain. While this type of risk management could offset losses due to adverse weather, it could not eliminate the losses. In addition it could be costly to implement such a diversification strategy.

4.2 Contract contingencies

An alternative to the use of advanced risk management tools is to simply pass the risk on to customers. For example, some construction companies have now started to pass their weather-related price volatility on to their customers through each projects contract.

This strategy may work very well in boom times, when construction labour is a scarcity. In not so good times, contract contingencies might be hard to accept for customers as they are free to pick among a wide range of available construction labour. Other construction companies might offer contracts where the construction company bear the weather risk themselves or even contracts where the construction company have eliminated the weather risk through weather derivatives.

4.3 Commodity futures

Commodity futures have been used as a risk management tool for a long time, and are still widely used. However, a commodity future reduces risk by locking a future price, thereby removing price risk. As a result, if an energy reseller experiences a normal winter, a commodity future will work properly. Should the winter be abnormally warm on the other hand, demand for energy will fall, and as a result the energy reseller's revenues will decline. The commodity future hedge will probably work partly as energy prices tend to fall during a warm winter. However, the commodity future does not protect against the low demand, and the energy reseller will experience low revenues even though he used commodity futures to hedge risk.

In this case weather derivatives would be an appropriate risk management tool for the energy reseller as his revenues fluctuates with the weather. In short, commodity futures are useful for hedging price risk, but weather derivatives are better suited for hedging volumetric risk.

4.4 Weather insurance

While weather risk products appear to be relatively new, weather insurance related to catastrophic weather events has existed for decades. In general, weather derivatives cover low-risk, high-probability events, often defined by a standardized contract. Weather insurance on the other hand covers high-risk, low-probability events as defined by a highly tailored policy.

A negative aspect of weather derivatives is that the buyer has to know how and by how much his business is affected by the weather. If he misjudges how weather affects business, weather derivatives will not work properly as a hedge. More positively, the payoff on a weather derivative contract is solely decided by the movement in a contract's underlying, not by the actual loss incurred by the company buying a weather derivative.

The opposite is true for weather insurances. When a high-risk, low-probability event occurs, the insured company doesn't automatically get a payout. First the company have to prove a financial loss related to the event. This financial loss can be difficult to prove.

To summarize, weather derivatives are well-suited as a hedging-instrument if your business is sensitive to low-risk, high-probability event like for example a colder than usual summer, and if you know the monetary value of adverse weather. Weather insurance on the other hand, is well suited for high-risk, low-probability events like for example a flood or a hurricane.

As we can see from the previous Sections several risk tools offer similar features to weather derivatives. In terms of cost, competition in not so good times, ability to hedge demand and ability to fit the needs of the hedger, diversifications strategies, contract contingencies, commodity futures and weather insurances all have shortcomings compared to weather derivatives. From this we can say that there is a market for weather derivatives that no other weather risk tools have managed to cover.

5 WEATHER VARIABLES AND INDEXES

Weather comes in many forms, and each one affects different companies in different ways. To hedge the different types of risk, weather derivatives are based on a large assortment of weather variables. Weather derivatives can also be structured to depend on multiple weather variables.

5.1 Weather variables

The most commonly used weather variable is temperature, measured as hourly values, daily minimum or maximum, or daily averages. Daily average temperature is the most common variable, but also this variable is defined in more than one way. Most countries define daily average temperature as the average of daily maximum and daily minimum temperature. However, some countries also define daily average temperature as the weighted average of tree, twelve, twenty-four or more values per day.

In addition to temperature, wind, rain and snow are also commonly measured weather variables used to create a weather index. Weather indexes are in turn used as the underlying for a weather derivative. All that is required to create a derivative structure is a source of reliable and accurate measurements. Consequently, weather variables like number of sunshine hours, streamflow or sea surface temperature are also possible.

5.2 Degree day indexes

Degree day (DD) indexes originated in the energy industry, and were designed to correlate with the domestic demand for heating and cooling, which in turn impacted the demand for energy. A degree day is a temperature-based measurement calculated as the deviation of the average daily temperature from a pre-defined base temperature. The standard pre-defined base temperature is 65˚F, or 18˚C, which is considered to be the ideal temperature.

65˚F is actually equal to 18.33˚C, while 18˚C is equal to 64.4˚F. Since temperatures used for the case study presented later in this thesis are in Celsius degrees, temperatures will for simplicity from now on only be listed in Celsius degrees.

At temperatures below 18˚C people are expected to turn on heating, and above people 18˚C are expected to turn on air conditioning. Therefore the two most popular degree day measurements are heating degree days (HDD) and cooling degree days (CDD).

5.3 Cooling degree days (CDD)

CDD indexes developed as an estimate of the amount of energy required for residential space cooling during the summer season. Thus, a CDD-index is a measure of how hot it has been. HDDs are defined by (ElementRe, 2002g) as

$$Daily\ CDDs = Max\ [\left(\frac{\mathrm{T_{Max}} - \mathrm{T_{Min}}}{2} - T_{\mathrm{Base}}\right), 0] \qquad (5.1)$$

T_{Base} is the preferred reference temperature, T_{Max} is measured as the maximum recorded temperature throughout the day, while T_{Min} is measured as the minimum recorded temperature throughout the day.

5.4 Heating degree days (HDD)

HDD indexes developed as an estimate of the amount of energy required for residential space heating during the winter season, and are thus a measure of how cold it is. CDDs are defined by (ElementRe, 2002g) as

$$Daily\ HDDs = Max\ [\left(T_{\mathrm{Base}} - \frac{\mathrm{T_{Max}} - \mathrm{T_{Min}}}{2}\right), 0] \qquad (5.2)$$

As we can see from equation 1.1 and 1.2, the number of HDDs and CDDs per day has not got a specified upper limit, only a lower limit of zero which implies that HDDs and CDDs do not take negative values. One of the number of HDDs or the number of CDDs on a particular time and place is always zero, and both are zero when the temperature is exactly equal to the baseline temperature.

5.5 Energy degree days

Instead of using both HDDs and CDDs, certain end-users prefer measuring energy degree days (EDDs). EDDs are simply the cumulative total of HDDs and CDDs and can be calculated as shown in (ElementRe, 2002g)

$$Daily\ EDDs = \sum \left[Max\left(T_{\mathrm{Base}} - \frac{\mathrm{T_{Max}} - \mathrm{T_{Min}}}{2} \right), 0 \right] + \left[Max\left(\frac{\mathrm{T_{Max}} - \mathrm{T_{Min}}}{2} - T_{\mathrm{Base}} \right), 0 \right] \quad (5.3)$$

The advantage of using EDDs, instead of a mix of HDDs and CDDs, is that EDDs can give a “year-round” index for companies interested in protecting revenues both against poor summer and poor winter weather. In example, electricity suppliers’ revenues could be adversely affected by a cold summer due to lower electricity sales for cooling. In addition electricity suppliers’ revenues could be adversely affected by a warm winter as a result of lower electricity sales for heating. To hedge against these events, electricity companies might hedge by purchasing a weather derivative based on the EDD-index.

As these three abovementioned degree days are the most commonly used, they are illustrated below with a table showing the calculations of CDDs, HDDs and EDDs based on temperature data from Oslo, and a baseline, $\mathrm{T_{base}}$, of 18°C. DD indexes will further be displayed in Figure 2, Figure 3 and Figure 4for the period 2006-2008, together with the average temperature for the same period, to easily see the relation between CDDs, HDDs and temperature.

Table 1 **Illustration of how Daily and Index-values of CDDs, HDDs and BDDs are calculated**

Date	T-Min	T-Max	T-Avg	CDDs	Σ CDDs	HDDs	Σ CDDs	EDDs	Σ CDDs
July 1, 2008	10.7	23.2	16.9	0.0	0.0	1.1	1.1	1.1	1.1
July 2, 2008	13.9	24.1	19.0	1.0	1.0	0.0	1.1	1.0	2.1
July 3, 2008	12.5	28.4	20.5	2.5	3.5	0.0	1.1	2.5	4.5
July 4, 2008	17.4	28.7	23.1	5.1	8.5	0.0	1.1	5.1	9.6
July 5, 2008	16.7	29.5	23.1	5.1	13.6	0.0	1.1	5.1	14.7
July 6, 2008	11.3	18.4	14.9	0.0	13.6	3.2	4.2	3.2	17.8
July 7, 2008	9.5	11.9	10.7	0.0	13.6	7.3	11.5	7.3	25.1

Figure 1 **Average temperature for Oslo**

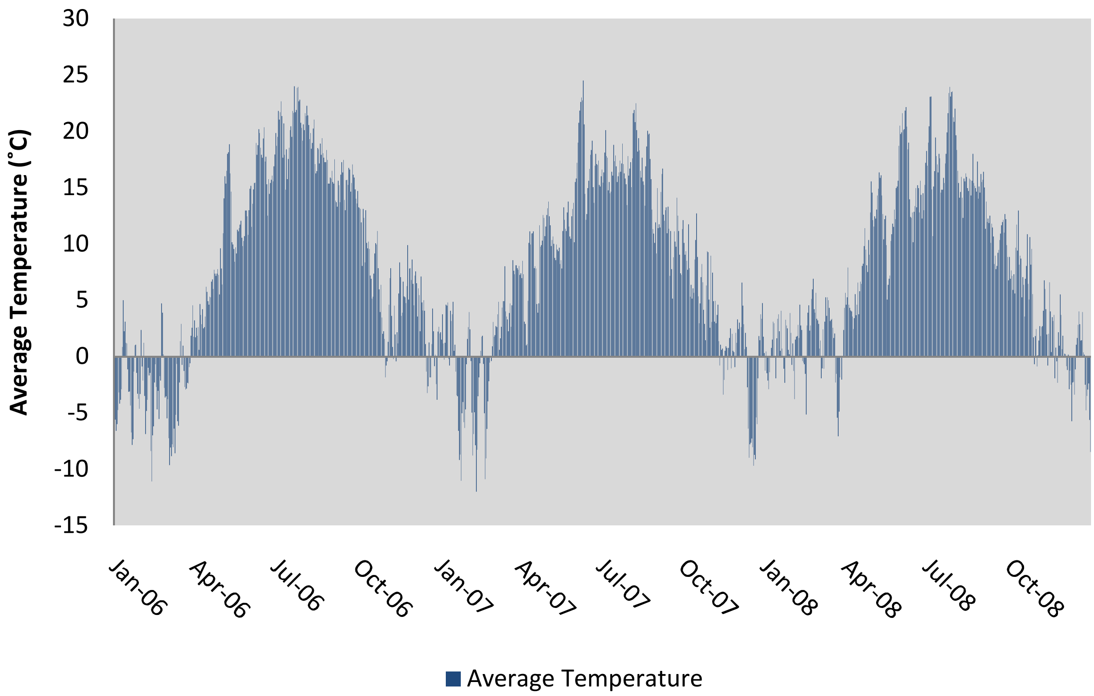


Figure 1 shows the average temperatures for Oslo. We can easily see that not many days in the year have an average temperature above 18°C. CDDs are days where the average temperature is above the chosen baseline of 18˚C. CDDs for Oslo are displayed in Figure 2. Figure 2 explicitly reveals that there are not too many days in the year with average temperatures above 18˚C. Days with average temperatures above 18˚C are mainly limited to the month of July.

Figure 2 **Daily CDDs for Oslo**

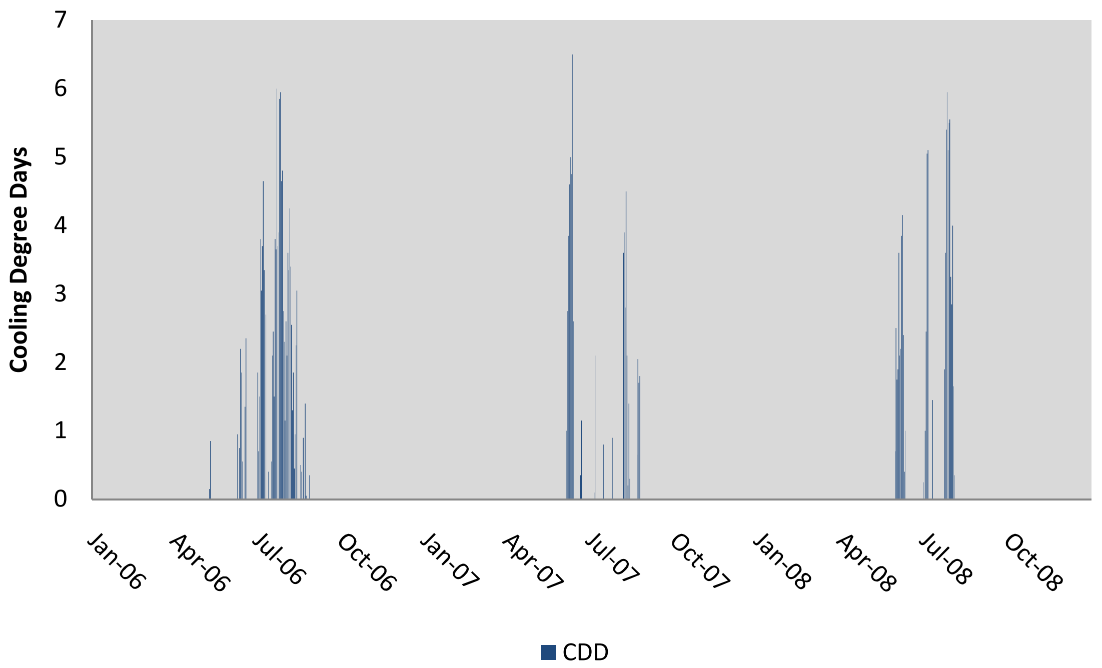
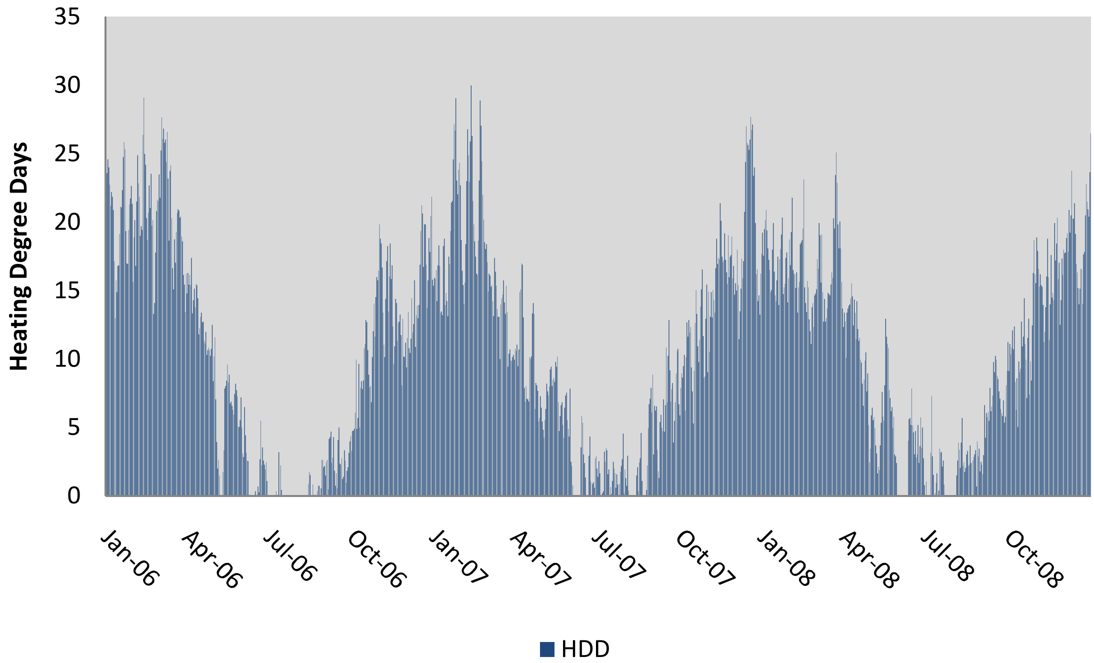
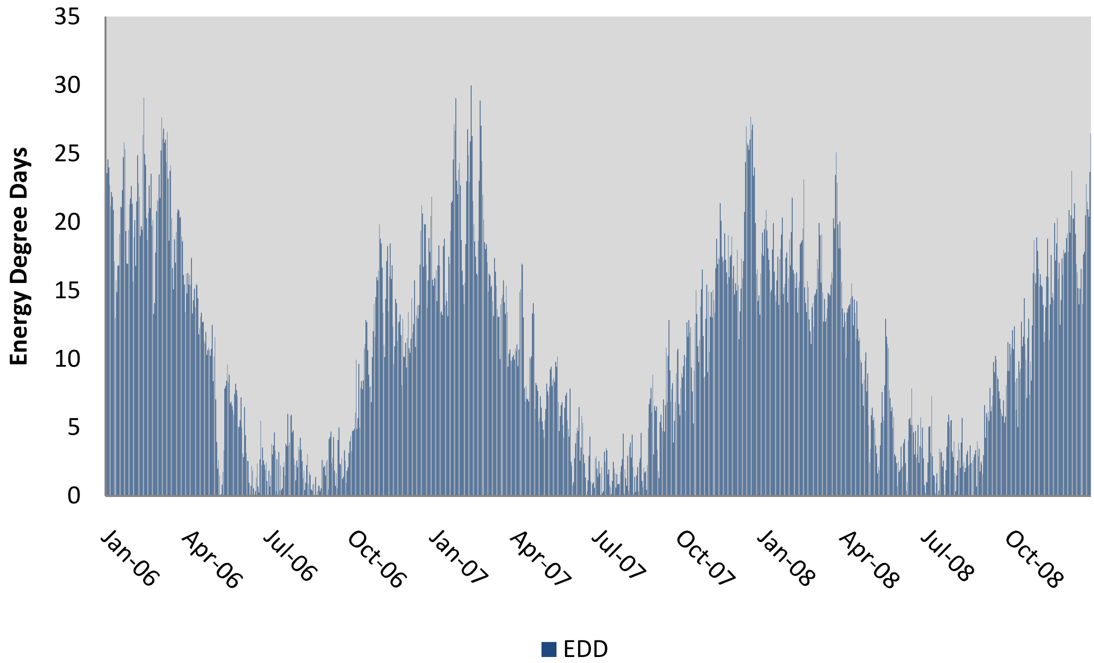


Figure 3 **Daily HDDs for Oslo**



From Figure 3 we can see that there is a large number of HDDs in Oslo, and that HDDs are spread throughout the year, with July month being the only month where some days are not a HDD. This can also be recognised from Figure 1 which shows the average temperatures, as HDDs are days where the average temperature is below the chosen baseline of 18˚C.

Figure 4 **Daily EDDs for Oslo**



From Figure 4 we can see that the number of EDDs in Oslo are quite high, and spread throughout the year. There are few EDDs in the summer months, as average temperatures then are close to 18˚C. This can also be seen in Figure 1 which shows daily average temperatures for Oslo. EDDs are days where the average temperature deviates from the chosen baseline of 18˚C. Days with temperatures close to 18˚C will result in a low level of EDDs.

5.6 HDD/CDD/EDD-indexes

Normally contracts do not cover single days, but longer periods like a month or season. Therefore the underlying of a weather derivative contract is an index of the chosen variable. The most common variables are HDDs, CDDs and EDDs. Indexes of these variables are defined as the sum of HDDs, CDDs or EDDs over all days during the period where N_d is the number of days in the period which the index covers (ElementRe, 2002g).

$$CDD - Index = \sum_{i=1}^{N_d} CDD_i \tag{5.4}$$

$$HDD - Index = \sum_{i=1}^{N_d} HDD_i \tag{5.5}$$

$$EDD - Index = \sum_{i=1}^{N_d} EDD_i \tag{5.6}$$

While HDDs and CDDs in 2005/2006 were the by far most popular underlying variable, accounting for as much as 97% of the notional value of contracts, there are also several other underlying variables used for weather derivatives (PriceWatherhouseCoopers, 2006). Even though other underlying variables just accounted for 3% of the notional value of contracts, weather derivatives on other underlying variables than HDDs and CDDs accounted for as much as 46% of the number of contracts. The distribution of types of contracts will be discussed in detail later, but first an introduction of less frequently used weather variables.

5.7 Beverage degree days

While HDDs, CDDs and EDDs are designed to be used by the energy sector, a similar index, based on BDDs, is used by beverage producers. Additional beverage consumption is not triggered at the same level as use of heating. A common assumption is that additional beverage consumption is triggered at 15 ˚C, and that beverage consumption increase for temperatures above 15 ˚C. Therefore the baseline for BDDs is set to 15 ˚C.

BDDs are defined as

$$Daily\ BDDs = Max\ [\left(\frac{\mathrm{T_{Max}} - \mathrm{T_{Min}}}{2} - \mathrm{T_{Base}}\right), 0] \tag{5.7}$$

where $\mathrm{T_{Base}}$ is the trigger level of 15 ˚C where increasing temperatures start to result in increased sales. A BDD-index is defined as

$$BDD - Index = \sum_{i=1}^{N_d} BDD_i \tag{5.8}$$

5.8 Growing degree days

An index similar to the previously mentioned indexes is used in the agricultural sector. Plants require certain amounts of heat to move from for example seed to fruit, while insects require certain amounts of heat to move from egg to adult, therefore GDD baselines are explicitly defined for different crops and insects as they have specific development thresholds and temperatures that must be reached in order for growth to continue. GDDs are defined by (ElementRe, 2002g) as

$$Daily\ GDDs = Max\left[\left(\frac{\mathrm{T_{Max}} - \mathrm{T_{Min}}}{2} - \mathrm{T_{Base}}\right), 0\right] \tag{5.9}$$

where $\mathrm{T_{Base}}$ is the threshold temperature which must be reached in order for organisms to grow.

A GDD-Index is defined as

$$GDD - Index = \sum_{i=1}^{N_d} GDD_i \tag{5.10}$$

5.9 Event indexes

Event indexes are defined as the number of days during the contract period that a certain metrological event occurs. Very exotic event indexes are often designed and traded over-the-counter (OTC). Rain-, snow- and wind-measurements are common weather variables. Rain-based hedges are used in the agricultural sector and by hydropower generation companies, among others. Snow-based hedges are important for ski resorts, snow removal companies and companies that sell equipment related to snow. Wind-based hedges are of interest to the growing number of wind farms which want protection against lack of wind, while construction companies might want protection against having to stop work in high winds.

Weather variables such as number of sunshine hours, humidity streamflow or sea surface temperatures are also used, but not very often. All that is required is a source of reliable and accurate measurements for a derivative structure to be created.

For example, contracts depending on the number of frost days, in this example defined as days where the temperature measured at 7 a.m. is below -3.5 ˚C, from November to March excluding weekends and holidays, have been developed as insurance for construction workers whom in many cases cannot work as usual on frost days.

5.10 Average of average temperature indexes

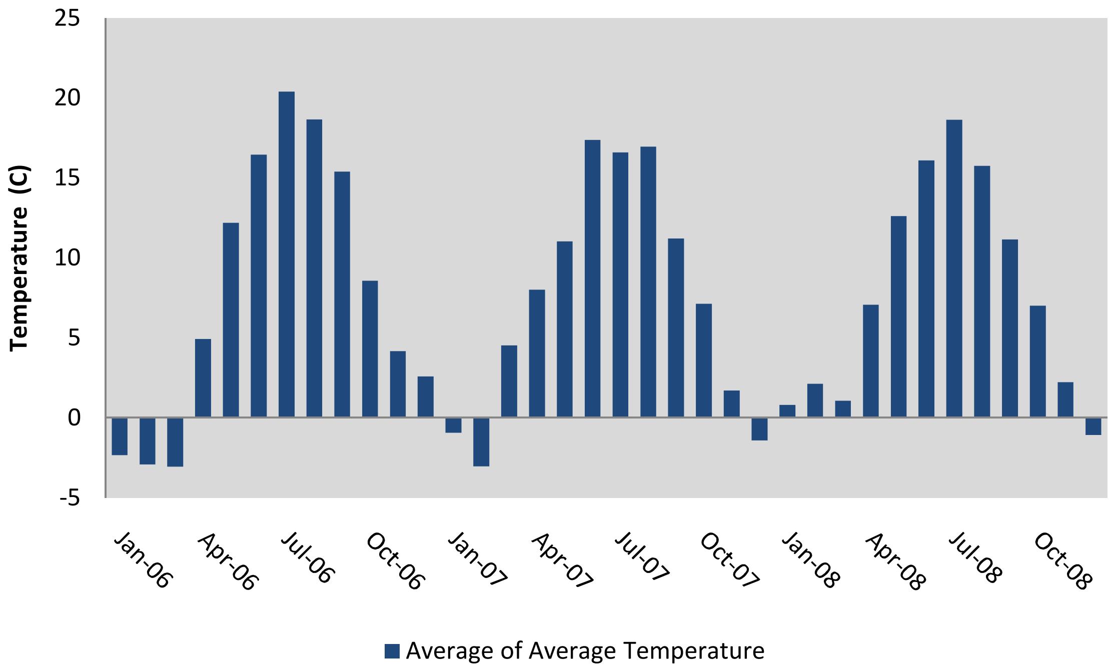
In addition to weather derivative contracts on different sorts of degree days, there are two ways of measuring the weather that are not very common in the United States, but frequently used in Europe and Japan. The volume of such contracts is limited now. Still, the measurement types are included since the use of them is expected to increase as the weather derivative market continues to grow rapidly in both Europe and Japan.

Average of average temperature indexes are calculated without the use of any baseline to be a more intuitive measure of temperature variability than degree day measures which are calculated from a baseline of 18˚C. Average of average temperature indexes are defined as the average of the daily average temperature values and are calculated as shown by (Jewson, Brix, & Ziehmann, Weather Derivative and the Weather Derivatives Market, 2005e)

$$\bar{T} = \frac{1}{N_d}\sum_{i=1}^{N_d}\frac{T_{Max}+T_{Min}}{2} \qquad (5.11)$$

Average of average temperature indexes are mainly used in Japan, but are rarely seen in the United States and Europe.

Figure 5 Monthly Average of Average Temperature Index for Oslo



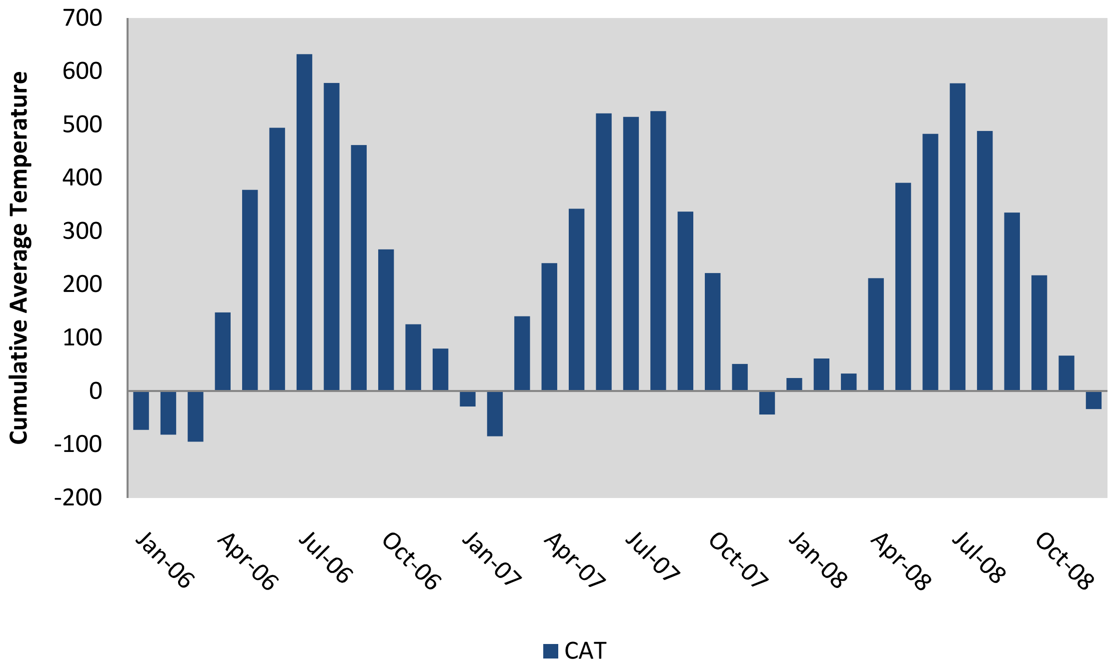
5.11 Cumulative average temperature indexes

Cumulative average temperature (CAT) indexes are defined by (Jewson, Brix, & Ziehmann, Weather Derivative and the Weather Derivatives Market, 2005e) as the sum of the daily average temperatures over the period of the contract

$$x = \sum_{i=1}^{N_d} \frac{T_{Max} + T_{Min}}{2} \tag{5.12}$$

CAT indexes are only used in Europe in the summer.

Figure 6 **Monthly Cumulative Average Temperature Index for Oslo**



6 MARKET PARTICIPANTS

The weather derivative market is a fairly new market, not well known by many. Even though the market still is relatively small, the span of providers, users and potential users is wide. Therefore the main players, both by industry and specifically by name will be briefly presented.

6.1 PROVIDERS

The weather derivatives market originates from the energy sector as the sector realized they faced considerable weather risk. Therefore quite naturally, some of the key players are still from the energy sector. Energy companies are natural end-users of weather derivatives, but as a result of several factors, among them lack of liquidity in the market and high premiums on weather derivatives, companies like Enron and Koch (via Entergy-Koch Trading) together with Aquila remain vital providers in the weather derivatives market.

Insurers and reinsurers have been involved in catastrophic weather risk coverage for decades, but have only recently entered the non-catastrophic weather market. Most insurers act as sellers of weather derivatives in order to diversify their portfolio. AIG, SwissRe, AXA, American Re and several other insurers participate in the weather derivatives market.

Insurers generally have a higher appetite for risk than other providers in the weather derivatives market. Insurers are exposed to very little weather risk compared to the risks they are exposed to in other areas of insurance. Hence, there is a large chance that future demand for risk capacity will be covered by insurers.

While insurers supply weather products that satisfy many corporate end-users, not all insurers are ready to manage a portfolio of high-probability, low-risk events. In addition, several end-users prefer to deal in derivatives rather than insurance. As a result, several hybrid companies offering derivatives, insurance and conversion of insurance to derivatives have formed. These hybrid companies tend to be active traders and portfolio risk managers. Examples of hybrid companies are Commercial Risk Capital Markets and Element Re.

6.1.1 Banks

Banks are playing an important role in the weather derivatives market as they have customers exposed to weather risk, and experienced staff that can structure, price and market risk products. In other words, banks can increase both the demand for weather protection through an increased number of end-users, and they can increase the weather risk capacity by offering weather risk products. Banks with an appetite for risk can purchase weather derivatives itself, while banks with less of an appetite for risk can do like BNP Paribas and establish several funds that invest in alternative asset classes, including weather derivatives (ElementRe, 2002c).

As more end-users require protection for weather exposure, available capacity may become a constraint. Hence marketing weather derivatives through banks are very important to ensure sufficient risk capacity in the weather derivatives market. It is therefore very positive that US banks like Goldman Sachs, JP Morgan Chase and Merrill Lynch now have a presence in the weather risk market.

Brokers themselves don’t directly offer weather derivatives, still they play a very important role in the market. They act as matchmakers in the market finding weather derivative providers for customers requiring weather derivatives. Initially the number of brokers outnumbered market participants by two to one, and quite obviously a consolidation had to come. Now TFS and United Weather are the dominant brokers in the weather risk market.

OTC-brokers played a crucial role in providing weather derivatives during the first year of the weather derivatives market. Still, it was not before Chicago Mercantile Exchange started to offer weather derivatives on its Globex platform the number of trades really started to spike.

6.1.2 Chicago Mercantile Exchange

At first weather derivatives were traded over-the-counter, directly between the parties. September 1999, the world's first exchange-traded weather derivatives started trading on the Chicago Mercantile Exchange (CME) (ElementRe, 2002a). Through CME's Globex electronic trade platform one could trade standard futures and options on temperature indexes in 10 different US cities. CME introduced electronic trading of weather derivatives with the intention of enlarging the size of the weather derivatives market, and to remove credit risk related to OTC weather contracts (Considine, 2004).

CME contracts attracted new participants and increased the liquidity in the weather derivatives market since the possibility of smaller transaction sizes substantially expanded the selection of potential users of weather derivatives. CME trading also allowed the investor to track his investment since weather options and futures are quoted in real time and can be accessed online by everyone. In addition CME trading through an electronic system that needs relatively little personal to operate comes at much lower trading costs than OTC-trading. On top of that, credit risk for participants is practically eliminated with the use of a clearing house system.

6.2 END-USERS

End-users can be roughly divided into two broad groups, hedgers and investors.

It is widely acknowledged that financial markets punish negative earnings surprise harder than they benefit a positive earnings surprise of similar magnitude (ElementRe, 2002d). For that reason risk managers hedge non-core risks like foreign exchange, interest rates, commodities, equities, credit, natural catastrophes, and now also weather. The focal goal of risk management is to increase shareholder value. Stakeholders prefer less volatile earnings stream to volatile earnings stream. Therefore companies that minimize earnings volatility, mainly through removing non-core risk, accomplish higher equity multiples, stronger credit ratings, lower cost of debt and improved access to funding.

Companies have managed price risk for years. Volumetric risk on the other hand, is a relatively new topic. Volumetric risk can be defined as variability in supply and / or demand caused primarily by variability in the weather (ElementRe, 2002d). While companies with volumetric risk have been hedged against catastrophic weather for years, non-catastrophic risk like normal variations in temperature or precipitation have until recently not been hedged. With increased weather and climate awareness, stakeholders and analysts acceptance of non-catastrophic weather risks have diminished. In some weather-sensitive industries, such as energy, ignoring weather risk is no longer accepted, and this point of view is starting to spread to other industries as well.

Table 2 **Examples of Links between Weather and Financial Risk**

Risk Holder	Weather Type	Risk
Energy Industry	Temperature	Lower sales during warm winters or cool summers
Energy Consumers	Temperature	Higher heating/cooling costs during cold winters and hot summers
Beverage Producers	Temperature	Lower sales during cool summers
Building Material Companies	Temperature / Snowfall	Lower sales during severe winters (construction sites shut down)
Construction Companies	Temperature / Snowfall	Delays in meeting schedules during periods of poor weather
Ski Resorts	Snowfall	Lower revenue during winters with below-average snowfall
Agricultural Industry	Temperature / Snowfall	Significant crop losses due to extreme temperatures or rainfall
Municipal Governments	Snowfall	Higher snow removal costs during winters with above-average snowfall
Road Salt Companies	Snowfall	Lower revenues during low snowfall winters
Hydro-electric power generation	Precipitation	Lower revenue during periods of drought

(Climetrix, 2002)

Table 2 summarizes the links between weather and financial risk for various industries. Next a more detailed description of the link between weather and risk for each industry will follow.

6.2.1 Natural gas

Natural gas is used for many purposes, but its main purpose, especially in the United States, is home heating during the winter months. Local distribution companies that deliver natural gas to home consumers are exposed to weather risk. Their business model is to buy supply contracts which they sell more expensively to their customers. This business strategy leaves sales volume as the main variable impacting revenues. Sales volume and temperature are highly correlated. A colder than normal winter leads to increased demand for natural gas. while a warmer than normal winter results in reduced demand for natural gas.

The most relevant index for seasonal gas volumes is aggregated seasonal heating degree days (HDDs). Since local distribution companies are hurt by warmer than normal winters they often buy HDD puts with strike set at, or slightly below, an average HDD-index related to their winter budget.

6.2.2 Electric utilities

Electricity is delivered to commercial, industrial and residential customers, and is used for core needs like heating in the winter and air conditioning in the summer. Electricity utilities revenue fluctuates with demand for electricity, making electricity utilities highly exposed to weather risk.

In addition, since electricity is generated from various sources like thermal, hydro, nuclear and wind, the electricity supply side is also exposed to weather risk. Consider a worst case example where an extremely dry year in Norway, results in low levels of water in the various water reservoirs and low supply capacity. Instead of exporting excess capacity to Europe, Norwegian electricity utilities would have to import electricity from Europe, leading to a substantial cutback in revenues.

Electricity utilities are exposed to weather risk, both through supply and demand. Exposure to weather risk combined with the import and export possibilities through the relatively new power markets, makes usage of weather derivatives quite complicated for electricity utilities, thus it will not be explained in detail here. However, roughly it can be said that since electricity utilities are exposed to warm winters, they protect themselves by buying HDD puts or collars, or sell HDD swaps. To protect themselves against a cold summer they buy CDD puts or collars, or sell CDD swaps.

6.2.3 Construction

Adverse weather may hinder the progression on a construction site. Precipitation and snowfall may be an obstacle to the operation of heavy machinery, while extreme temperatures may affect the laying of concrete and masonry.

Construction contracts are often designed with incentive clauses, often based on the date of completion. If the construction company finishes ahead of time, they are rewarded a predetermined amount per day. Opposite, if the project is finished after the deadline, the construction company pays a predetermined penalty per day. Adverse weather is the single most common reason for missed deadlines, making weather derivatives highly relevant for construction companies (ElementRe, 2002d).

Contractors are often given a normalized number of days by which it can exceed its deadline due to adverse weather. In cases where such normalization days are not granted, the contractor can buy weather derivatives to cover any penalties that may occur, and build the derivative premium into the cost of the bid.

Hedges for the construction industry are usually based on adverse construction days (ACDs) over the planned construction period. The underlying in such contracts can be rainfall / snowfall in excess of predetermined daily amount, temperature above / below a predetermined daily level, or a combination of the two. As contractors are highly aware of incentive amounts attached to the construction contract, ACD-hedges are often constructed to replicate the profitability of a construction contract.

6.2.4 Offshore operations

Industries that conduct offshore or marine operations are exposed to both catastrophic and non-catastrophic weather. Property damage caused by catastrophic weather can typically be covered by property and casualty insurance. Business interruption caused by strong wind can be covered by non-catastrophic weather risk products.

Drillers who generate revenues based on the amount of oil or gas they extract per day immediately feels the effect of adverse weather. A hedge can be created based on storm track indexes where the wind level that interrupts business is used as a strike. Such a hedge would give offshore operators the possibility to obtain a certain financial coverage even on days with adverse weather.

6.2.5 State and municipal government maintenance operations

State and municipal governments are particularly exposed to weather risk through their obligation to remove snow during the winter season. Snow removal costs are generally included in a budget, however the true cost of snow removal will depend on aggregate seasonal snowfall or the number of snow clearing days.

If the government employ outside contractors, cost to the government is often related to the total amount of snow cleared during the season. For government-employed snow removal labour, costs incur as a function of snow clearing days (SCDs). That is, days where the amount of snow is sufficient enough to create hazardous driving and walking conditions which the public authorities have to confront.

A government may use calls on SCDs, with payouts equal to estimated cost of labour, salt and fuel for each SCD to hedge against the number of snow clearing days in a winter season.

6.2.6 Agriculture

The agricultural sector is exposed to weather risk as crops require certain conditions to develop properly. Most crops need a minimum cumulative amount of heat to fully develop, measured by a growing degree (GDD) index. The number of GDDs also determines the timing of harvest. A low GDD index results in reduced yield and quality of the crop. In addition, late harvesting drastically increases the possibility of being exposed to heavy rainfall in the autumn, which in turn would lead to further reductions in yield.

A possible hedge would be a weather derivative with multiple triggers. The farmer can buy a protection based on precipitation exceeding a certain amount of centimetres, which is effective only if actual GDDs are less than required to harvest the crop.

A more specific example, in June 2008 the World Bank created a weather derivative allowing Malawi, one of the poorest countries in the world to hedge against drought (The World Bank, 2008). In case of a drought, Malawi's maize crops are at risk, and in 2005 a drought brought widespread hunger to several countries in Southern Africa. A weather derivative hedge against drought gives Malawi financial protection against future droughts. A weather derivative hedge also reduces the probability of a hunger crisis, which might be a more effective way of helping than addressing immediate needs when a drought hits Malawi and destroys the maize crops.

6.2.7 Food and beverage

Manufacturers, bottlers, packagers and distributors of soft drinks, beer and bottled water have revenue heavily dependent on sales volume. Sales volumes tend to increase as temperature and humidity increase, but only above a threshold level. An index based on beverage degree days (BDDs), with a baseline set at a temperature or humidity level where people start to buy more beverages can be created. Further, the BDD index can be used as the underlying in a weather derivative hedge.

Within the food industry, seasonal products like soup and ice cream are heavily exposed to weather risk, more specifically to temperature. As with beverages, the temperature effect only comes into place above or below a certain threshold level, since there is always a segment of the population that will eat ice cream and soup. Sales volumes first start to increase as temperature move above or below the relevant threshold level, and a hedge should be based on an index with the relevant threshold level as a baseline.

6.2.8 Retailing

Sellers of seasonal products, such as winter coats and beach apparel, are highly sensitive to weather conditions in the season for which their goods are designed.

Retailers selling summer apparel are exposed to the risk of both cool temperatures and rainy weather. Their primary exposure is to the number of rainy days during the season rather than total amount of precipitation. To hedge exposure to rainy days, they may purchase calls on rain event days (REDs).

Most retailers depend on customers to physically visit their shop. Hence retailers are exposed to inclement weather such as cool temperatures and heavy snowfall which may hinder potential customers from visiting retailers' outlet. Retailers can hedge against these conditions by purchasing protection against adverse retail days (ADRs). An ADR index is an index with multiple triggers based on temperature falling below a predetermined level, or accumulated snowfall above a given number of centimetres.

6.2.9 Manufacturing

Manufacturers of seasonal products are exposed to the same weather risk as retailers. However, while retailers often have a diversified portfolio of products, manufacturers are often more specialized. This makes manufacturers of seasonal products like ski equipment, umbrellas, heaters, air conditioners and road salt highly exposed to weather risk.

In addition manufacturers often give weather-linked guarantees to their customers to improve customer-vendor relationships by covering the cost of unsold or unused inventory. Manufacturers can also use weather derivatives to hedge the weather-linked guarantees given to their customers.

6.2.10 Outdoor entertainment

For players in the outdoor entertainment industry weather is a crucial input for certain kinds of entertainment. Ski resort operators depend on the weather to drive the number of paid skier visits in a season. Obviously, the most important weather input for ski resorts is snow, but consumer behaviour in weekend resorts differs from consumer behaviour in destination resorts. Weekend resorts are defined as resorts where customers come on rather impulsive trips, while destination resorts are more planned trips where skiers fly in. Weekend resorts rely heavily on weather conditions as an impulsive ski trip easily can be cancelled in case of adverse weather. Destination resorts on the other hand are not as exposed to the weather from day to day, but they are exposed to the accumulated snow fall as their customers rely on natural snow conditions.

Other outdoor entertainments highly exposed to adverse weather, in these cases rain, are golf courses, theme parks, concerts and fairs. All mentioned operators are expected to suffer a loss of customers and revenue in case of a rainy day. To hedge away this risk, a call on rain event days (REDs) can be bought.

6.2.11 Transportation

The transportation industry is exposed to adverse weather, such as heavy snowfall, rain or fog, which may lead to costly delays. With heavy snowfall the risk of accidents increases for automobiles and trucks. As a consequence the speed of transportation is reduced. The airline industry are highly exposed to weather risk both through conditions on the ground like accumulated snowfall, and through visibility conditions which often aren't good enough during heavy snowfall or periods with fog. As the airline industry is heavily exposed to weather risk, the most advanced and accurate weather stations are often located at or nearby airports, giving airlines a wide range of opportunities to hedge against adverse weather.

To hedge against adverse weather a customized index called flight cancellation days (FCDs) can be created based on weather events such as snowfall, rain and fog, with notional values based on the estimated financial cost of delays. Once the specific conditions of an FCD are defined and the risk quantified, the airline can buy calls on FCDs, which would give the airline financial compensation when weather conditions indicated a flight delay.

6.2.12 Banks and insurance companies

In addition to acting as market-makers, commercial and investment banks may also be end-users. As end-users banks utilize weather products to hedge commitments and risk undertaken in the normal course of business.

For example, banks may be exposed to weather trough financing weather-sensitive projects, such as a hydro power plant. If most of a loan is to be repaid by weather-sensitive cash flows, most of the default risk is pure weather risk. With an existing portfolio of loans, a bank may purchase a weather hedge to improve credit quality of the portfolio. Either by a hedging loan-by-loan or by hedging the aggregated weather risk of the portfolio.

Banks also offer hybrid financing products, such as loans with embedded weather derivatives linked to customers' cash flows. Hybrid financing products offer a low coupon in periods where adverse weather negatively affects the customer's cash flow. The low coupon is financed partly by the weather derivative which kicks in due to adverse weather. In periods with normal weather, the weather derivative provides zero payoff, and the customer pays a slightly higher coupon than through standard financing options. However, this is manageable as normal weather indicates normal cash flows.

6.2.13 Investors

Many companies in the stock market are affected by weather. Individual stocks of companies exposed to weather risk, that do not hedge themselves against adverse weather is expected to be correlated with the weather that affects them. Still, different companies are affected in different ways by the weather. As a result a diversified portfolio of stocks is expected to have little or no correlation to the weather. This expected lack of correlation is also confirmed in a German study which concludes that short-term stock-returns are not affected by local weather (Krämer & Runde, 1997).

A weather derivative study by Cao, Wei and Li compared efficient frontiers for a portfolio of equities, a portfolio of equities and bonds, a portfolio of equities, bonds and commodities to a portfolio of equities, bonds, commodities and weather derivatives. The efficient frontier for the latter portfolio outperformed all the other portfolios in terms of risk and return (Cao, Wei, & Li, Weather Derivatives: A New Class of Financial Instruments, 2003).

In another study Cao, Wei and Li analysed correlation of temperature in New York versus several financial markets (Cao, Wei, & Li, Watching the Weather Report, 2004). The study was performed on data from 1992 to 2002. The study compared temperature in New York to the performance of North American, European and Pacific equity indexes, US Government bonds and Goldman Sachs commodity index. As we can see from Table 3 the study clearly suggests that there is zero, or close to zero, correlation between weather and financial markets.

Table 3 Correlation between Temperature and Financial Markets

	N. America	Europe	Pacific	Bond	Commodity	Temperature	μ	σ
N. America	100%						9%	16%
Europe	38%	100%					5%	15%
Pacific	10%	35%	100%				2%	18%
Bond	0%	-1%	-5%	100%			1%	4%
Commodity	-1%	-3%	2%	-8%	100%		0%	17%
Temperature	2%	-1%	-2%	-1%	-1%	100%	0%	10%

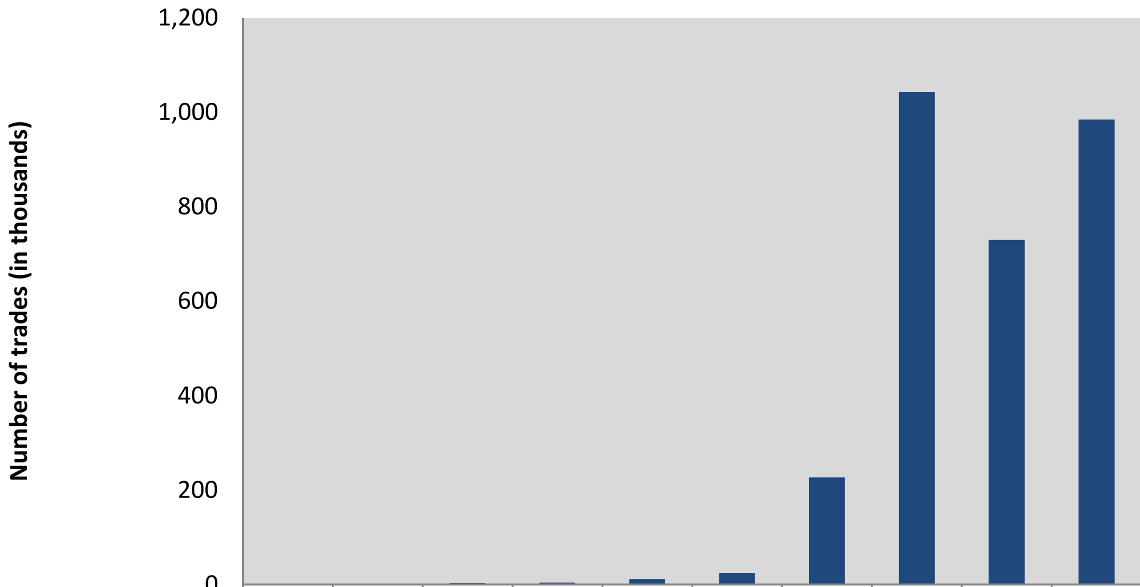
The issuance of large amounts of sovereign and corporate debt, co-ordination on international monetary policy, investment across markets and borders, implementation of quantitative arbitrage strategies driven by powerful computing resources, indexation of derivative products allowing large funds to quickly switch between asset classes, and dissemination of critical financial news on a global real-time basis, have helped forge much closer ties between global asset markets. As a result investment returns generated by various products such as equities, debt and currencies in various markets such as US, Europe and Asia are becoming increasingly correlated (ElementRe, 2002d). As a consequence investors are seeking investment strategies that generate returns uncorrelated with those in the traditional financial markets. This new area is referred to as alternative investment management. Alternative investment management include among others, catastrophic and non-catastrophic weather as these have little correlation with traditional financial markets.

Despite low correlation to traditional financial markets investors can receive attractive returns as new hedgers enter the market and soak up capacity. New capacity can be created by offering returns in excess of the risk investors have to bear. As investors become more comfortable in weather derivatives trading, it is reason to believe they will place a greater percentage of their assets in this asset class to achieve the high returns offered through weather derivatives.

7 CHARACTERISTICS OF TODAYS WEATHER DERIVATIVES MARKET

The first weather derivative was traded in 1997, but the number of weather derivative trades only recently started to boom. PriceWaterhouseCooper's annual survey of the weather derivative market, both OTC-trades and trades through CME, shows that after a relatively slow start, the number of weather derivative trades skyrocketed 827% from 2004 to 2005. This was followed by an increase of 359% from 2005 to 2006. Although 2007 showed a 30% decline in number of trades from 2006, the number of trades in 2007 was still far higher than all other previous years. Market intelligence indicates that the peak value record from 2005/6 was mainly caused by a build up and liquidation of the weather portfolios of three large US-based speculators (Roth, Ulardic, & Trueb, 2007). From 2007 to 2008, the weather derivatives market again experienced a robust increase of 35% in the number of trades. According to the Weather Risk Management Association (WRMA) the main contributors to growth are that the weather derivative market is growing both geographically and in diversity of participants as more and more sectors, especially the agriculture sector, are trying to offset their exposure to weather risk (Reuters, 2008).

Figure 7 Historical number of weather derivative trades

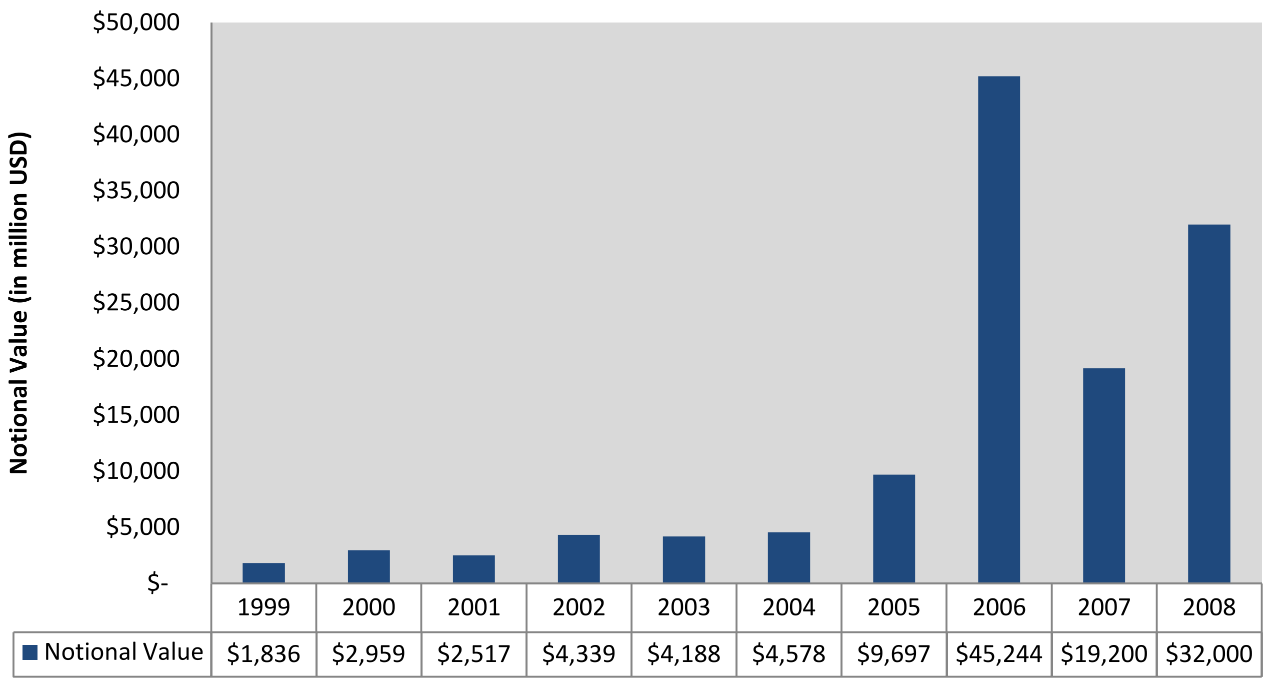


	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Number of trades	1	1	3	4	12	24	227	1044	730	985

The number of weather derivative trades is strongly correlated with the total notional value of all weather derivative contracts. However, as the value of each weather derivative contract can vary very much, it is useful to have a look at the total notional value of all contracts traded throughout the year to get an understanding of the growth in the market.

The notional value for a swap contract is defined as the maximum contingent payment to a company, plus the maximum contingent payment to the counterparty. For trades without contingent payments, the notional value was either defined as a notional value agreed to by both parties to the trade, or the maximum potential loss based on the appropriate weather measure over the last 25 years (PriceWatherhouseCoopers, 2006).

Figure 8 **Historical notional value of weather derivative trades**

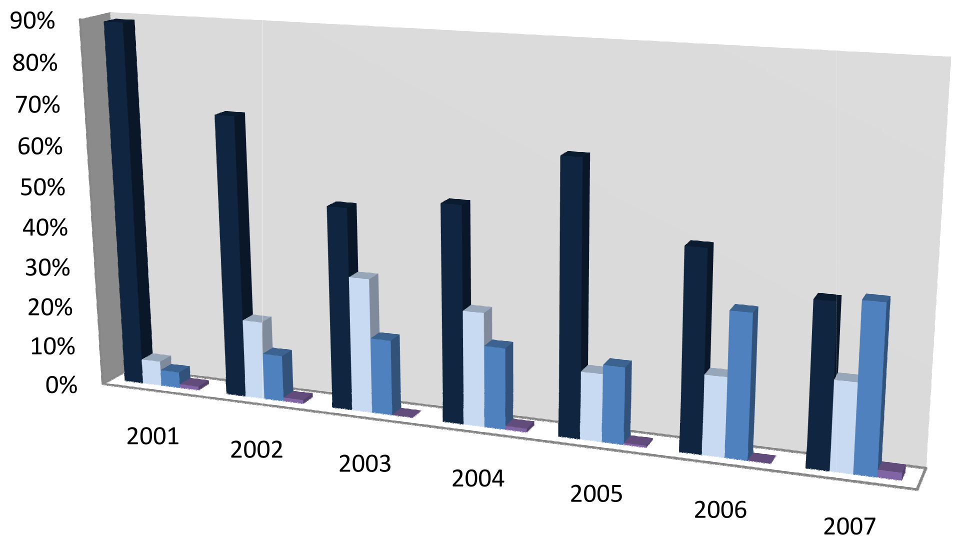


Considering the small market for weather derivatives at the time, the growth in notional value of all weather derivative contracts was not very impressive up until 2004. However, from 2004 to 2005 the market experienced a solid increase of 112%, followed by a jump of 367% from 2005 to 2006, resulting in a total notional value of $45.2 billion. From 2006 to 2007 the total notional value of contracts plunged 58% to $19.2 billion. It is worth noticing that the number of trades dropped only 30% over the same period, which indicates that the 58% drop in notional value partly was caused by a drop in number of trades, and partly because the average contract value was much lower in 2007 than in 2006. The lower average contract value might be a result of some big weather risk management players not being as active as in 2006. From 2007 to 2008, the weather derivatives market increased 67% in notional value, compared to 35% increase in number of trades, indicating that the average contract value is increasing again. If the previous assumption related to the average contract value is correct, a higher average contract value indicates that the big weather risk management players are becoming more active again.

7.1 Geographical dispersion

The weather risk market started in the US energy sector, so quite naturally US companies dominated the market in the start. Numbers from PwC's annual survey of the weather derivatives market show a geographic expansion of business. 2006/7 showed a rough 40/40/20 split between North America (including Canada) / Asia / Europe, while the same statistics for 2001/2 showed a rough 90/5/5 split.

Figure 9 **Historical distribution of OTC-contracts by region**



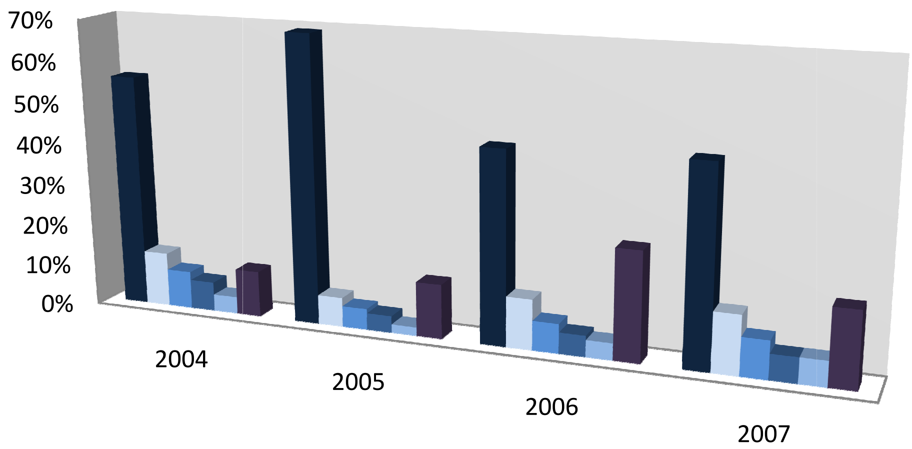
	2001	2002	2003	2004	2005	2006	2007
North America	89.1%	68.7%	49.1%	52.2%	65.2%	47.4%	38.3%
Europe	6.1%	19.1%	32.61%	27.4%	16.1%	18.7%	20.9%
Asia	3.9%	11.3%	18.26%	19.6%	18.3%	33.9%	39.1%
Other	0.9%	0.9%	0%	0.9%	0.4%	0%	1.7%

Even though these statistics indicate that weather derivatives are starting to get as common in Europe and Asia as they are in North America, this is probably not the entire truth. With the introduction of weather derivatives trading on CME, the number of OTC-contracts has slowly started to decline, accounting for only 2,180 out of 1,043,619 weather derivative contracts in 2006. As 26 out of the 41 cities on which CME offers weather derivative products are in North America, and since CME also offer a wider range of weather risk products on the North American cities, there is reason to believe that an overweight of the contracts traded on CME are traded in North America.

A shift in North American trades from OTC to CME would imply that the geographical expansion hasn't been as good as one might think by looking at Roth, Ulardic & Trueb's numbers. Still, there is a positive side to the assumption. The geographical expansion is far lower than indicated by the dispersion of OTC-contracts by region, this would imply a very large growth potential in Europe, Asia and Other geographical regions.

7.2 Participation by industry

Figure 10 Distribution of potential end-users by industry



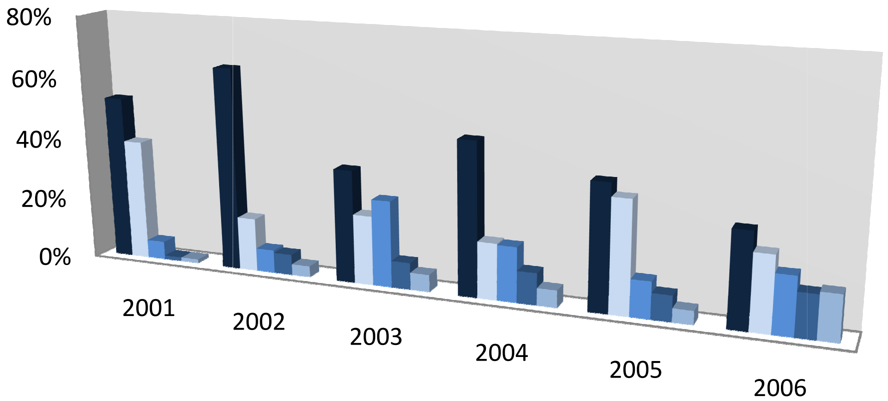
	2004	2005	2006	2007
Energy	56%	69%	46%	47%
Agriculture	13%	7%	12%	14%
Retail	9%	5%	7%	9%
Construction	7%	4%	5%	6%
Transportation	4%	2%	4%	6%
Other	11%	13%	26%	18%

Figure 10 reveals that the interest in weather derivatives is growing for all industries. Even though the energy sector now accounts for less of the potential end-users in percentage, it is important to keep in mind that the weather derivatives market have grown rapidly recently. So even though the energy sector now accounts for less of the weather derivative trades, the interest for weather derivatives is still growing within the energy sector. It is just not growing as fast as it is in other sectors.

7.3 Distribution of Contract Types

In Section 7.2 we looked at who the most dominant industries in the weather derivatives market are. Based on the dominant industries and their exposure to weather we get a rough idea of which contract types are the most popular. Figure 11 displays an historical overview of the most frequently traded contract types in the OTC-market.

Figure 11 Distribution of Number of Contracts by Type (OTC-market only)



	2001	2002	2003	2004	2005	2006
HDD	53%	65%	36%	49%	40%	30%
CDD	39%	17%	22%	18%	36%	24%
Other Temp	6%	7%	28%	18%	12%	18%
Rain	1%	7%	9%	10%	8%	14%
Other	1%	4%	5%	5%	4%	14%

Not surprisingly HDD- and CDD-contracts have been, and are, the most popular contract types. This is as expected since the energy industry is the most dominant industry in the market, and mainly trade in HDD- and CDD-contracts. It is also worth noticing that more alternative contract types like Rain and Other are growing in popularity. The growth in alternative contracts in the OTC-market might come as a consequence of a shift in trade in HDD- and CDD-contracts from the OTC-market to CME. Next we will examine the notional value of contract types in the OTC-market, and in the total market including CME.

Figure 12 Distribution of Notional Value of Contracts by Contract Type (OTC)

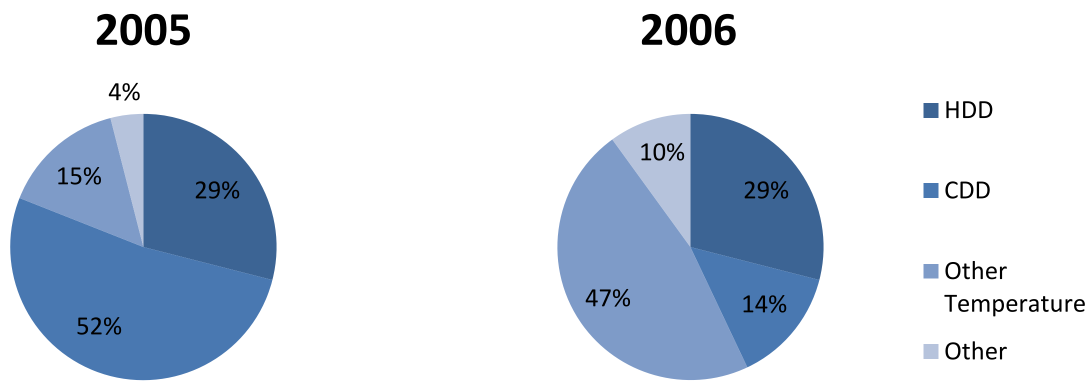
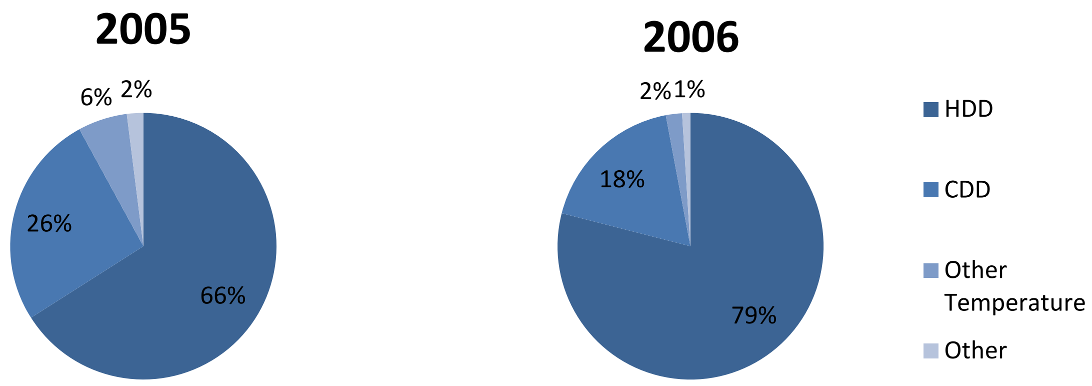


Figure 13 Distribution of Notional Value by Contract Type (OTC & CME)



Earlier we have seen that CME is the leading market place for weather derivatives. We have also seen that the energy industry is the dominant industry within weather derivatives. The most important contract type for the energy industry, especially in the US, is HDDs to hedge against a warm winter. Therefore it is not surprising that HDDs are by far the most dominant contract type on CME, as seen in Figure 13. Contracts used to hedge against a warm winter can be fairly standardized, and as all the largest US cities are listed on CME, energy companies can buy their HDD-hedges from CME.

CDD-contracts are currently the contract type best suited for standardization. This has an accelerating effect as more products and locations are listed on CME. From Figure 7 and Figure 8 we could see that weather derivatives grew significantly in popularity after they started trading on CME. While contracts other than temperature contracts are quite popular in the OTC-market, accounting for 28% of the contracts in 2006, they only accounted for 3% of the notional value on CME in 2006. If the weather derivative market continues to grow, more products and more locations will be listed on CME. Listing of new products and locations is a source of growth for the weather derivatives market as this makes products more easily available to end-users.

8 CLEANING AND DE-TRENDING DATA

Without high quality data weather derivative valuation becomes close to impossible. One always have to check the quality of a dataset before using it for weather derivative valuation, and several times one will discover the dataset is not flawless. In such cases cleaning of data is necessary. Some of the most common problems are missing data and unreasonable data such as maximum temperature lower than minimum temperature. To remove such problems, data from neighbour weather stations should be used. Alternatively a time series approach can be used. A time series model is built based on data from the used weather station, and problem data points are filled in via the model.

Due to phenomena like global warming, industrialization, urbanisation and moved weather stations, several weather datasets will contain trends. For example, most geographical locations have been a victim of global warming the last decades. As a result they experience higher average temperatures today than they did fifty years ago. Using fifty years of weather data will therefore underestimate the average temperature for the given location. If this difference is not accounted for before valuation of a weather derivative, the weather derivative will be mispriced. To account for trends one need to de-trend the dataset used for weather derivative valuation.

Choosing the length of the dataset is also a challenge. In general one can say that the more data available the better. However, recent observations are often more relevant than old observations. As one use larger datasets the weighted importance of recent observations is reduced. The choice between focusing on recent observations or a large dataset is an individual decision that needs to be made case by case.

9 WEATHER DERIVATIVE VALUATION

Unlike option pricing, where Black and Scholes option pricing formula is considered a universal formula (Black & Scholes, 1972), weather derivative valuation has not yet a single formula which is widely accepted as the right way to price weather derivatives. Several suggestions to how weather derivatives should be priced have been published. "Pricing Weather Risk" (ElementRe, 2002f), "The Black-Scholes Equation for Weather Derivatives" (Jewson & Zervos, The Black-Scholes Equation for Weather Derivatives, 2003) "Weather Derivatives Valuation and Market Price of Weather Risk" (Wei & Cao, 2004), and "Weather Derivative Valuation" (Jewson, Brix, & Ziehmann, Weather Derivative Valuation, 2005c) are some of the most cited works on weather derivative valuation. Still, none of the valuation methods have yet managed to achieve universal acceptance. It is worth noticing that weather derivative contracts in a portfolio of weather derivatives or related to a specific hedging strategy, have additional complexity as can be seen in Section 2.5 on modelling a hedged portfolio. Next, some of the most common valuation methods will be presented, along with a discussion why they should or should not be used as a weather derivative valuation method.

9.1 Risk premium

Before we describe the most common weather derivative valuation methods a discussion on risk premium is required. As shown in Table 3 there is little or no correlation between weather and financial markets. Wei and Cao argue that in theory, since investors can diversify all risk in a weather portfolio, no risk premium should be required (Wei & Cao, 2004). In another article Cao, Wei and Li point out that risk premiums can represent a significant part of the derivative's value (Cao, Wei, & Li, Watching the Weather Report, 2004). Therefore, just discounting the expected payoff by the risk free rate may incur sizeable errors. Further they draw attention to the fact that risk premiums are higher for options than futures. Higher risk premiums for options come as a result of option non-linear payoff. In line with arguments from Cao, Wei and

Li, a study by Härdle and Cabrera concluded that the risk premium in the weather derivative market differs from zero and is positive (Härdle & Cabrera, 2009).

Financial theory implies that since nearly risk in a weather portfolio can be diversified, zero market premium should be charged. Still, empirical findings contradict this theory. Empirical findings of a positive risk premium make sense as the weather derivative market is still rather illiquid. Consequently, if a company wanted to entirely diversify their weather portfolio this would probably be very hard to achieve.

Next a very alternative approach to estimating a risk premium is presented. Weatherbill provides weather derivatives over-the-counter through their online portal Weatherbill.com. Quotes for a wide range of contract types can be requested online. What would Weatherbill charge for a contract that for certain would result in a payout? To test what Weatherbill would charge a quote was requested on the 18th of June. The specific contract was to pay $100 if the minimum temperature in Oslo on the 23rd of June was below 50 ˚C. The daily minimum temperature in Oslo has never been above 30 ˚C, so it seems fair to say that it is 100% certain this contract will give a $100 payout. The option premium charged by Weatherbill for the contract was $110. If we ignore problems related to NPV calculations due to the short period of time, we can say that Weatherbill charge $110 on the 18th of June to pay $100 on the 23rd of June. The $10 difference is the risk premium required by Weatherbill. This is a highly alternative approach to estimating a risk premium. However, empirical studies of the risk premium for weather derivatives are extremely limited. Consequently, a 10% risk premium seems as reasonable as any other random number, and a 10% risk premium will be used in the chapter on applied weather derivative valuation.

9.2 General pricing theory

In ElementRe's book on weather risk management Henderson gives a brief overview on considerations to take when pricing weather derivatives (ElementRe, 2002f). The price of a derivative can in general be written as

$$P = E(P) + R(P) \tag{9.1}$$

where E(P) is the expected payoff on the derivative. If option premiums equalled the expected payoff, providers and end-users of weather derivatives would in the long run achieve break-even. R(P) is the derivatives' risky payoff, a random variable with an expected value of zero. R(P) is often referred to as the risk premium and depends on the risk preferences of providers and end-users.

$$Price_{\frac{Bid}{Offer}}(t) = D(t,T)\left[E(P) \mp F_{\frac{Bid}{Offer}}(R(P))\right] \tag{9.2}$$

where $D(t,T)$ is the discount factor. A potential payoff will first be paid at contract maturity, T. Thus we need to discount the expected payoffs and required risk premium to present value. $F_{\frac{Bid}{Offer}}$ is a function that represents the risk preferences of end-users and providers. $F_{\frac{Bid}{Offer}}$ is often described by risk aversion in combination with method of measuring risk, for example standard deviation. If we assume that the provider is risk averse, or in best case risk neutral we can say that

$$F_{\frac{Bid}{Offer}} \geq 0 \tag{9.3}$$

As explained in Section 2.5 on portfolio theory, the risk premium required by a provider will depend on the provider's current portfolio (CP). The same derivative could increase total portfolio risk for one provider while it could reduce total portfolio risk for another provider. To account for this R(P) should be a function of the current portfolio, CP. In cases where a derivative would reduce total portfolio risk we get

$$F_{\frac{Bid}{Offer}} \leq 0 \tag{9.4}$$

A negative function for risk preferences would imply that the provider achieves a sufficient reduction in total portfolio risk and therefore is willing to sell the derivative at a premium lower than the expected payoff.

Finally, a transaction may be part of a hedging strategy. A hedging strategy may be static or dynamic. In both cases a hedging strategy will have costs related to putting on and maintaining hedges. Therefore hedging strategies should be included as a factor when pricing weather derivatives. In the end, the payoff P, becomes a function of the hedging strategy HS.

$$Price_{\frac{Bid}{Offer}}(t) = D(t,T)\left[E(P(HS)) \mp F_{\frac{Bid}{Offer}}(R(P(HS),CP))\right] \tag{9.5}$$

where the expected payoff is a function of historical payoffs, P, and hedging strategy, HS. The risk premium is a function of hedging strategy, HS, and current portfolio position, CP.

Assume a provider has no other assets in his portfolio. Also assume that the weather derivative is on an illiquid index so that hedging is impossible. μ is the expected payoff. If we assume the provider's risk preferences can be measured by standard deviation of returns, and that the level of risk aversion is given by the Sharpe-ratio, α, we get

$$\mathrm{Price}_{\mathrm{Bid}}\ (\mathrm{t}) = \mathrm{D}(\mathrm{t},\mathrm{T})[\mu + \alpha\sigma] \tag{9.6}$$

$$\mathrm{Price}_{\mathrm{Offer}}\ (\mathrm{t}) = \mathrm{D}(\mathrm{t},\mathrm{T})[\mu - \alpha\sigma] \tag{9.7}$$

In words, the price is the discounted value the expected derivative payoff, with a bid-offer spread proportional to the standard deviation of historical derivative payouts.

9.3 Historical Burn Analysis

Historical burn analysis (HBA) is the simplest form of weather derivative valuation. HBA is based on the idea of evaluation of how a contract would have performed in previous years. HBA can be applied to raw or de-trended weather data, and HBA on raw data is the simplest form of weather derivative valuation.

A brief recipe on how to apply historical burn analysis is

1. Collect historical weather data
2. Convert weather data into Degree Days
3. Make necessary adjustments to the dataset
4. Calculate the implied option premium for each year in the period

5. Calculate the average implied premium
6. Discount back to settlement data

By performing these six steps we reach a risk neutral option premium based on historical burn analysis. This is the simplest form of HBA.

While it is quite obvious that one would not attempt to use an average from one or two data points, the sufficient amount of data points is not clear. One quantitative method to assign a confidence level to historical averages is to compute standard error values. To calculate a rough estimate of the standard deviation of the estimated mean is given by the formula

$$\text{Standard Error} = \frac{\sigma_{\text{Historical Payout}}}{\sqrt{\text{N}}} \qquad (9.8)$$

where N is years of data used (ElementRe, 2002f).

Standard error of the mean payout is largely decided by the number of observations, N. By entering the desired level of standard error, and the calculated $\sigma_{\text{Historical Payout}}$ into the equation above, and solving with respect to $\sqrt{N}$ we get required number of observations to achieve the desired level of standard error.

Historical burn analysis suffers from two competing effects. Increasing the number of observations, N, will reduce standard error of the mean, which is desirable from a statistical point of view. However, more recent observations of temperature may be more relevant than older points. In some cases it might therefore be more appropriate to use few, but recent, observations.

9.3.1 Assumptions behind Historical Burn Analysis

If we take it for granted weather index data used for calculations are correct, and properly de-trended, we only need to make a single assumption to use HBA. We have to assume that weather index values for different years are independent and identically distributed.

One-month contracts are separated by eleven months, three-month contracts are separated by nine months and five-month contracts are separated by seven months etc. In Europe the autocorrelation of climate anomalies is close to zero after a month, implying that for contracts up to eleven months of duration, there is no autocorrelation on such contracts (Jewson, Brix, & Ziehmann, The valuation of single contracts using burn analysis, 2005d).

In the United States, climate autocorrelations last up to at least six months, mainly due to El Niño, an oscillation that disrupts regional and global climate patterns over longer periods (Jewson, Brix, & Ziehmann, The valuation of single contracts using burn analysis, 2005d). If El Niño's effects are not removed from historical data, the assumption that weather index values for different years are independent and identically distributed is not valid. However, such effects can be removed, and this justifies the assumption of independence of years for contracts up to eleven months.

For contracts with twelve months duration, the last days of the year are correlated with the first days of the next year; hence it is inappropriate to assume independency. Still, this is not a big problem as twelve-month contracts are very rare.

While historical burn analysis is great when you want to get a rough estimate of the price of a weather derivative, it often returns a huge standard deviation. Even with a large number of years used the standard deviation tends to be high. Therefore, in most cases, more accurate valuation methods are needed.

9.4 Index models

While historical burn analysis gives a rough estimate for the weather derivative value, statistical modelling of the weather might be used for more accurate weather derivative valuation. If we can find a suiting statistical distribution for a dataset, we can run a large number of simulations to estimate the average payout, rather than being restricted to the available dataset. Much can be written about index modelling, but index modelling as described by (Jewson, Brix, & Ziehmann, The Valuation of Single Contracts using Index Modelling, 2005a) can also be briefly summarized

1. Collect historical weather data
2. Convert weather data into Degree Days
3. Calculate HDDs or CDDs for given periods
4. Fit the index distributions to a statistical distribution by use of statistical distribution function methods
5. Create a pricing formula for the derivative you want to price for a selected analytical distribution function of HDD or CDD.
6. Calculate the derivative price by using Monte-Carlo simulating
7. Discount back to settlement date

Statistical modelling can in principle be used at any stage of the settlement process of a weather derivative. For example a CDD-contract could be valued using a statistical model for daily maximum and minimum temperature, daily average temperature, daily CDD values, total CDD values or the payoff value.

Maximum and minimum temperature time series could be modelled as stochastic time series, but they tend to show significant cycles in mean and variance. In addition such temperature time series show autocorrelation. These statistical problems are hard to overcome, and even though methods could be used to circumvent the problems, this will not be done here as we have other options.

Average temperature is simpler to model as there is now only one time series to model and therefore no autocorrelations. Still average temperature also shows seasonality and autocorrelation of the observed temperatures, making the time series challenging to handle. Again, since we have other options, weather derivatives will not be valued here using daily average temperatures.

Minimum, maximum and average temperatures might be normally distributed. That is clearly not the case for daily CDDs as the baseline used to calculate CDDs creates a cut-off. Since daily CDDs can't be fitted to normal distribution it is likely that a statistical model will be complex, so again, since we have other options, no statistical model for daily CDDs will be considered.

The most widely used method by practitioners is to use accumulated CDD values. For accumulated CDD values consecutive years are relatively independent and the distribution of values is reasonably smooth and tractable, implying that the total CDD values might be modelled using a univariate distribution.

For swaps modelling the payoff is almost the same as modelling the index, but modelling the index is preferred as the index distribution has smooth tails, while the payoff distribution for capped swaps stops at the limiting values. For options the distribution will consist of a spike at strike value and this could be difficult to model, so index modelling is preferred.

As it is clear that the values used for statistical modelling should be index values, the next step is to determine the probability distribution that best fits the de-trended index data. Fitting a distribution to historical index data is a matter of trial and error. First a few guesses are made and then suggested distributions are tested by distribution fitting tests like the Chi-Squared test and Quantile–Quantile (Q-Q) plotting (D'Agostino & Stephens, 1986). A test of the appropriateness of normal distribution on historical index data is to compute skewness and kurtosis for the historical index data. If skewness and kurtosis for the historical data do not differ too much from zero, this is an indication that the data is normally distributed.

The next step after a statistical distribution is chosen for the historical data is to calculate parameters such as mean and standard deviation. These are then used in the final step where the index is simulated under the proposed statistical distribution. Such simulation is often referred to as Monte Carlo simulation.

The central limit theorem is an important statistical result. The central limit theorem shows that under some technical conditions, the sum of a large enough number of random variables will be normally distributed (Keller, 2006). In many practical situations, a sample size of 30 may be sufficiently large to assume normal distribution. In cases where we can assume that the sampling distribution is approximately normally distributed shows that the payout of a call or a put option with no limit on the payout can be found by

$$E_{Normal}(\mu,\sigma,\varphi,N_0,K) = N_0\left[\frac{\sigma}{\sqrt{2\pi}}e^{\frac{-(K-\mu)^2}{2\sigma^2}} + \frac{\varphi(K-\mu)N(\varphi(K-\mu)}{\sigma}\right] \qquad (9.9)$$

where μ is the mean of the underlying, σ is the standard deviation of the underlying, N_0 is the notional, K is the strike, φ is 1 for a call or -1 for a put, and N(.) is the cumulative distribution function for the standard normal, N(0,1) (ElementRe, 2002f).

The above equation gives the expected option payout. To arrive at the option premium a risk premium needs to be added to the expected option payout. Finally the sum of the expected option payout and required risk premium is discounted by the risk free rate to give the present value. The value we arrive at after discounting is the option premium.

A call with a limit on its payout can be written as a capped call (ElementRe, 2002f). That is a long call, capped with a short call at a higher strike, K. If the limit is L, the expected call value is

$$E_{Normal}(\mu,\sigma,\varphi,N_0,K,L) = E_{Normal}(\mu,\sigma,\varphi,N_0,K,) - E_{Normal}\left(\mu,\sigma,\varphi,N_0,K+\varphi\frac{L}{N_0}\right) \qquad (9.10)$$

9.5 Dynamical models

Temperatures are path dependent. If a new maximum temperature is recorded at time *t*, there is a high probability that also the next day will be hotter than average. Distribution analysis does not account for the path dependency of temperatures. Distribution analysis simulates future temperatures based on historical mean and standard deviation of temperatures. Distribution analysis is a useful tool, and might be used for several situations. However, there are at least three situations in which a dynamical model becomes necessary (ElementRe, 2002f).

9.5.1 Pricing under dynamic hedging

When we wish to compute the expected payout and standard deviation of a financial position and a dynamic hedging strategy we need to know more than just the final value of an index. We also need to know the dynamical process of the underlying variable. Information about the dynamics of the index is required to dynamically reduce or eliminate risk from our portfolio.

9.5.2 Pricing path-dependent contracts

Some weather derivative contracts are path-dependent. That is, payout on the contract depends on the index vale at more than one point during the contract period. Obviously, such contracts do not solely depend on the index distribution at individual times, but also on the relation between the index value from time *t*, to time *t+1.* Such contracts are priced similar to Asian options (McDonald, 2006).

9.5.3 Pricing index contracts in terms of more fundamental variables

Is a contract path-dependent? That depends on one's point of view. A seasonal call option on EDDs depends only on the EDD-index value at maturity. The call option is therefore not path-dependent as the underlying variable, the EDD-index value, is not path-dependent.

However, this can also be looked at differently. The EDD-index can be written as a sum of daily EDDs

$$EDD - Index = \sum_{t=1}^{N_d} EDD_t \qquad (9.11)$$

where EDD_i is the number of EDDs at time *t, and* t_1 and N_d are the first and last days of the contract period. While the EDD-index is not path-dependent, each observation of daily EDDs is path-dependent. If we want to calculate our values in terms of daily EDDs we need a dynamical model. Dynamical models are in general more complex than distribution analysis, but in return we achieve a more consistent pricing of different contracts.

Consider the valuation of weekly contracts for week 26 and 27. Use of distribution analysis will give derivative prices that are not interrelated. This is unlikely to be correct as a cool week 26 would increase the probability for a cool week 27. The problem of path-dependency can be circumvented by use of a dynamical model. A dynamical model would take the simulated weather for week 26 into consideration when pricing a contract for week 27. Hence, dynamical models assure more consistent contract pricing.

9.5.3.1 Simulations of the weather

To arrive at a dynamical model we need to simulate future weather. The purpose of a temperature simulation procedure is to quantify the distribution of future seasons from which the future will be drawn. To simulate temperature Dischel's D1 Stochastic Temperature Model for Valuing Weather Futures and Options will be used (Dischel, 1999).

Dischel's model simulates daily temperatures. Dischel suggests a mean-reverting model with three parameters.

$$T_{t+1} = \alpha\Theta_{t+1} + \beta T_t + \gamma\Delta T_{t,t+1} \tag{9.12}$$

where

$$\Theta_{t+1} = \frac{\sum_{Year} T_{Year,t+1}}{Number\ of\ years} \tag{9.13}$$

$$\Delta T_{Year,t+1,t} = T_{Year,t+1} - T_{Year,t} \tag{9.14}$$

The model might seem complex at first sight basically what the model says is that the temperature on 1st of July depends on the historical average temperature for 1st of July, the temperature on 30th of June, and the change in temperature from 30th of June to 1st of July.

The three parameters are the time-varying daily temperatures averaged over several years, Θ_{t+1}, the previous day's temperature, T_t, and the random daily change in temperature, $\Delta T_{t,t+1}$. α, β and γ are constants. Through simulation of multiple seasons we can use an optimization algorithm to determine the values of α, β and γ. Parameters are chosen so that statistics of the simulated data are close to statistics for historical data, subject to $\alpha+\beta=1$, and γ close to unity.

Once we have determined α, β and γ for the dynamical model we can use Monte Carlo simulation to simulate values of the random daily changes in temperature, $\Delta T_{t,t+1}$. As Θ_{t+1} and $T_t$are given by historical weather data we now have all inputs to calculate the next day's temperature with Dischel's model.

As soon as future temperatures have been determined the approach is similar to that of distribution analysis. Calculate the temperature-index value. Calculate implied option payoffs. Discount by risk free rate to achieve the risk neutral option price.

While this temperature simulation model is the most advanced weather derivative valuation method presented here, the model is still very simple compared to more extensive meteorological models. It is of course by far too inaccurate to be used for real meteorological weather forecasts, and probably relative simple to methods practiced by providers and end-users in the weather derivatives market.

10 Conclusive remarks on the weather derivative market

In Chapter 2 on hedging both theoretical and empirical evidence concluded that proper hedging has positive features. Further Chapter 3 revealed that weather derivatives may be used to manage weather risk in a way that no other risk management tool can, before several examples of corporations exposed to weather risk in a wide range of industries were presented in Chapter 6.

When hedging has a positive effect, weather derivatives are a unique risk management tool and a wide range of businesses are exposed to weather risk, why are weather derivatives not a more commonly used risk management tool?

By all means, weather derivatives have shown a remarkable growth over the last decade, both measured in absolute and relative terms. However, the total transaction volume of weather derivatives is insignificant relative to transaction volumes for other risk management tools like derivatives on commodities, interest-rates and currencies.

A major problem with weather derivative is the vast expertise required to use them. Most people in the financial world would have an idea how to value and use a derivative on interest rates or currencies. When it comes to weather derivatives financial skills are no longer enough. Extensive knowledge about meteorology and statistics is required to properly price a weather derivative, in addition to financial skills. Such a combination of knowledge is hard to find in any person. Certain companies might have this expertise available, but most likely only if the company actively seek such a combination of competence. As weather derivatives gain popularity, more people will learn about weather derivatives. It is reasonable to assume that the more people that knows about weather derivatives, the more potential providers and end-users there will be.

If the weather risk market managed to arrive at a universal formula to price weather derivatives, they might gain popularity. Currently several valuation methods are used, among them the distribution analysis and the dynamical model presented in Chapter 9. The lack of a universal model makes it very hard to analyse which estimates of future weather the counterpart have used when arriving at a bid or offer price. The lack of a universal model also makes it hard to choose which model oneself should use for weather derivative valuation. If someone was to derive a widely accepted model for pricing of weather derivatives, the author would expect a significant increase in popularity for weather derivatives.

CME is the dominant exchange for weather derivatives. Still weather derivatives are only listed for 41 cities worldwide. On a global basis very few are then able to hedge their weather risk through CME. They may turn to the OTC-market, but also this market seems to be somewhat limited in its geographical dispersion. As CME continues to list derivatives on this would be a natural source for further growth. As only 41 cities are listed so far one can say that the growth potential seems enormous. However, as mentioned before, weather derivative valuation requires high quality weather data. Currently weather data in Australia, Japan, the US and most of Europe holds sufficiently high quality. The rest of the world in general has a too short history of weather data, or the data measurements are not accurate or reliable. Still as meteorological measurements continue to approve around the world, more and more locations will become eligible for weather derivative trading.

Briefly summarized, the weather derivatives market has some challenging obstacles in finding a universally accepted valuation method, spreading knowledge about weather derivatives and providing high quality weather data on more locations than today. Nonetheless, if and when one or more of these challenges are properly dealt with, the weather derivative market offers unique products and seems to have a substantially potential for growth.

A CASE STUDY OF RINGNES AS

The previous chapters have presented some theory behind corporate hedging and weather risk management, with a particular focus on how weather derivatives can be used to hedge weather risk. In the following chapters this theory will be applied to a case study of the Norwegian brewery Ringnes AS. First the correlation between temperature and sales will be analysed. Then, based on the correlation a hedging strategy will be proposed. Finally the respective hedging instrument will be valued.

Revenue per litre sold is sensitive information to Ringnes. To avoid making this thesis confidential, numbers for gross profit per litre were used. Revenue is the amount received for an item, and should cover variable costs, fixed costs and hopefully some profit. Gross profit is revenue minus variable direct costs and should cover fixed costs and hopefully some profit. For a company in a tight financial situation large cutbacks in gross profit might swipe away all profits and in worst case jeopardize the ability to pay fixed costs

11 THE BUSINESS OF RINGNES AS

Ringnes AS, a subsidiary of the Carlsberg Group, is a Norwegian brewery from 1876 with a strong position in the Norwegian market for beverages. Ringnes mainly produce and distribute beer, soft drinks and water, which together account for 99% of their sales. Their main focus is on the Norwegian market, and almost all of their sales are related to this market. They have strong market positions throughout the country with solid brands as Ringnes, Carlsberg, Tuborg, Munkholm, Pepsi, Solo, Farris and Imsdal. Yearly Ringnes deliver approximately 400 million litres of beverages to the Norwegian people. Sales of beverages tend to have a seasonal pattern, and this pattern will next be analysed by looking at the correlation between beverage sales and weather.

12 PREPARING FOR ANALYSIS OF WEATHER AND BEVERAGE SALES

In this Section the correlation between beverage sales and temperature will be analysed. Data on beverage sales are provided by Ringnes. The beverage sales data is on weekly sales out of stores, and these will be matched with weekly data for temperature. Before we start the analysis of sales versus temperature we first need to decide from which locations the weather data should be from.

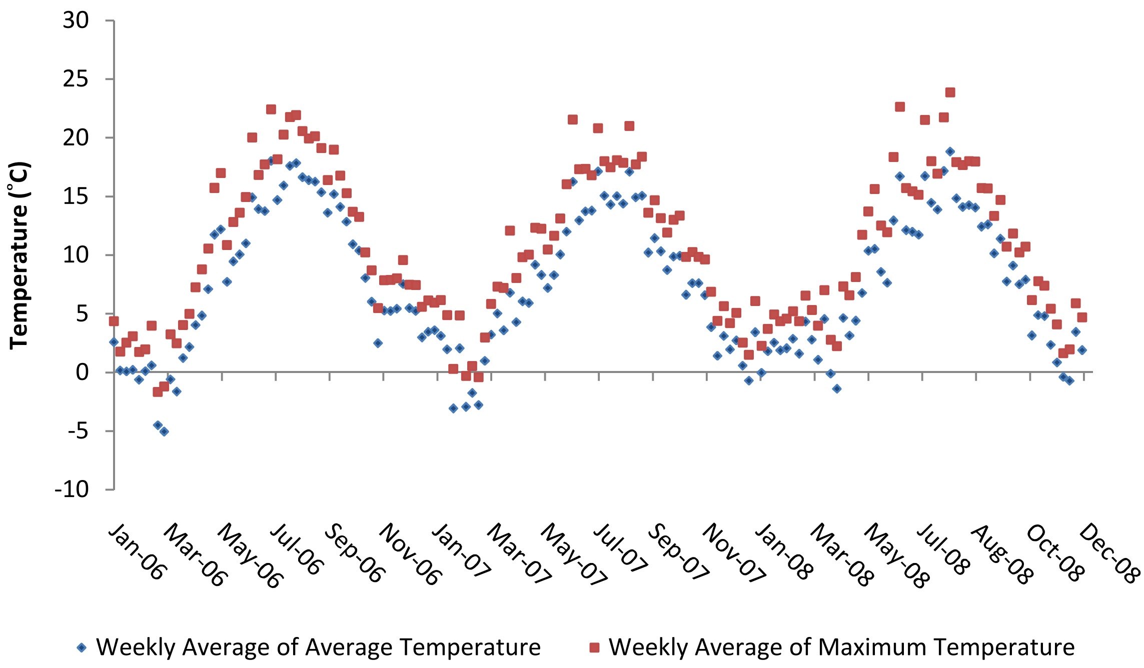
12.1 Choosing weather station

As Ringnes' sales are spread throughout the country, weather data from six of the most populated Norwegian cities were analysed. The cities were chosen based on population and geographical location relative to other cities used in the analysis. The cities used in the analysis were Oslo, Kristiansand, Stavanger, Bergen, Trondheim and Tromsø. Ringnes' sales are spread throughout the country. Therefore the original idea was to use an average of temperatures from several high populated cities. However, early analysis showed that this resulted in significantly worse results than by just using temperatures from Norway's biggest city, Oslo. Norway is a geographically big country, and temperatures in the north may differ significantly from temperatures in the south, just as temperatures in the west may differ significantly from the temperatures in the east. As roughly one fourth of Norway's population resides in the surrounding areas of Oslo, is seems just as reasonable to assume that Ringnes' sales would be closely correlated to temperatures in Oslo, as to an average temperatures from several cities. Therefore all temperatures used in the following study are from Oslo. More specifically from weather World Meteorological Organization station number 492, Oslo / Blindern.

12.2 Choosing the appropriate temperature measurement

There are three standards for measurements of daily temperatures. Daily temperatures can be measured as the minimum, maximum or average temperature throughout the day. The standard measurement method in weather risk management is to use average temperature, most often calculated as the average of maximum and minimum temperature. Nevertheless, in this analysis the goal is to map beverage consumption to temperatures. Beverages are in most cases consumed throughout the day. Therefore maximum temperatures during the day are more relevant than minimum temperatures during the night. To check if this somewhat alternative temperature measurement deviates significantly from the average temperature a correlation analysis of average temperatures versus maximum temperatures was performed.

Figure 14 **Weekly average temperatures vs. weekly maximum temperatures**



A correlation studies of average temperatures versus maximum temperatures for Oslo shows a correlation of 99,44%. The high correlation is also confirmed by Figure 14 where we can see the strong correlation between average and maximum temperatures. Based on these findings it seems appropriate to use maximum temperatures instead of average temperatures, which is the standard within weather derivative. The two measurements are highly correlated, but maximum temperature is a better measurement to map beverage consumption. Therefore maximum temperatures are used in the further analysis.

12.3 De-trending weather data

Use of historical weather data to price a derivative on weather in the future relays on the critical assumption that historical weather is a good approximation of future weather. Historical weather data often show clear trends. Often it is reasonable to believe that the trend will continue into near future. Use of average historical weather data will in such cases give poor estimates of future weather. To avoid poor estimates historical data should be adjusted for trends.

To be able to use historical weather data from Oslo in weather derivative valuation, we examined the data for trends. Fifty years of daily maximum temperatures was used in the analysis. First a linear regression was performed on daily values for fifty years. Linear regression is explained in detail in Section 12.5.1. The linear regression showed a positive trend, but due to seasonal patterns the results were not statistically significant. To circumvent the problem of seasonal patterns a separate regression was run on each day of the year for fifty years of data. The regressions showed contradicting results and were not statistically significant. Next, to reduce noise in the observations, a regression was run on average monthly maximum temperature. Eleven out of twelve months showed a positive trend, but again the results were far from statistically significant. Finally a regression was performed on yearly average temperatures for fifty years of data. The results are shown in Figure 15.

Figure 15 50-year trend in Yearly Average of maximum temperatures

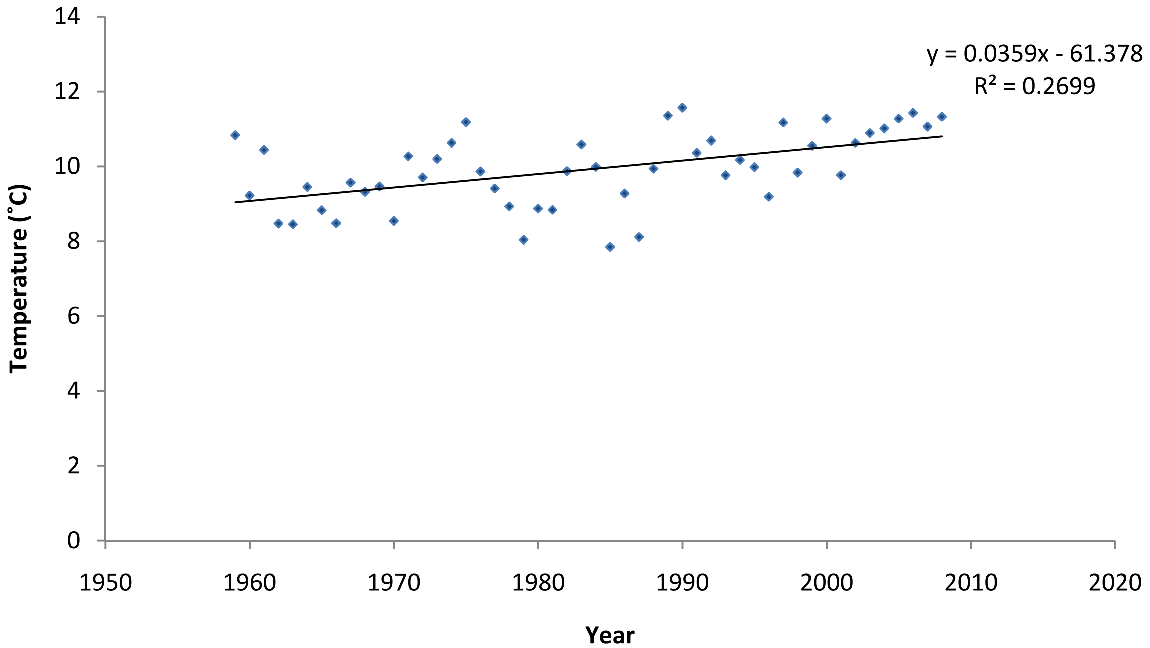


Figure 15 shows a clear upward trend in the yearly average of maximum temperatures. A T-stat of 4.21 and a p-value of 0.00 confirm that the results are clearly significant. The regression indicates an increasing trend in yearly average of maximum temperatures of 0.0359 ˚C per year the last fifty years.

Results from the regression above could be used for de-trending historical weather data. However, recent years of data might be a better indicator of the real trend of current weather data. Global warming and urbanisation would be two obvious reasons to explain the upward trend. These phenomena are of more recent date, hence using ten years of data to predict the trend seems more appropriate.

Figure 16 **10-year Trend in Yearly Average of maximum temperatures**

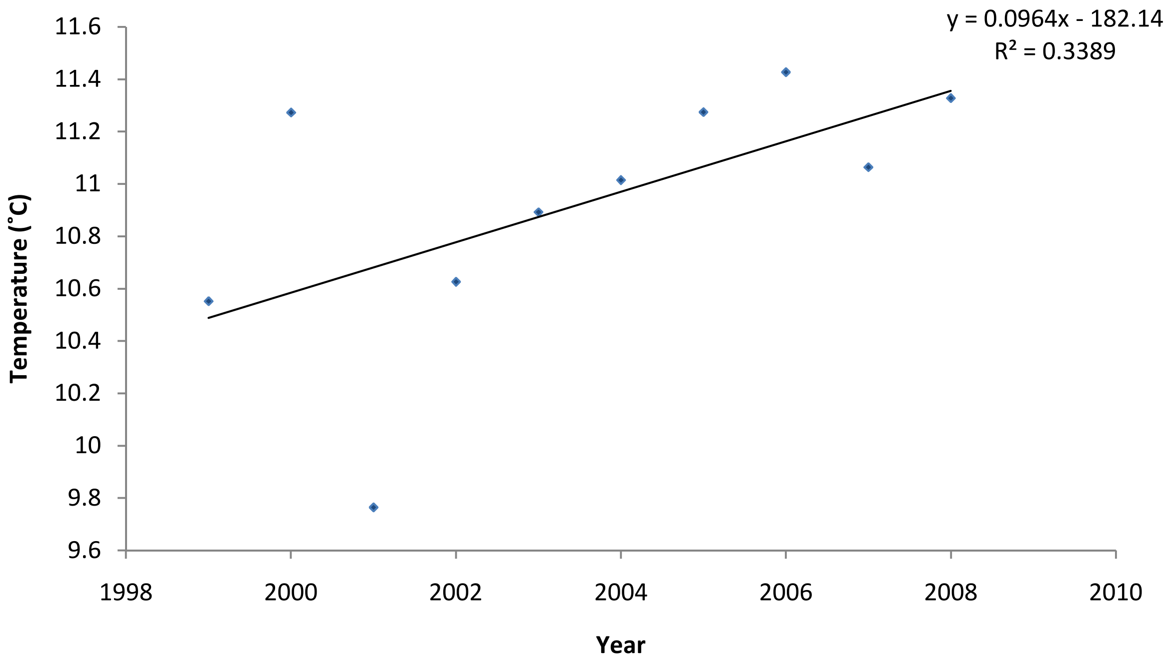


Figure 16 also shows an upward trend in yearly average of maximum temperatures. The coefficient of determination is slightly higher in this regression. Again results are statistically significant with a T-stat of 2.02 and a p-value of 0.08, meaning that the results are significant at a 90-% confidence level. Especially worth noticing is that this regression indicates a 0.0964 ˚C yearly increase in yearly average of maximum temperatures, which is a much stronger trend than found by using fifty years of data.

To de-trend historical data 0.0964 ˚C will be added to the daily maximum temperature one year prior to the final observation used in the regression. For the observation two years prior to the final observation used in the regression 2*0.0964 ˚C will be added etc. Temperatures don't all of a sudden make s shift of 0.0964 ˚C, so the trend will be smoothed throughout the year. This approach is of course just an approximation, but will give more accurate results than by not de-trending historical temperatures at all. All weather data used in the continuation of this thesis will be de-trended weather data.

12.4 Adjusting beverage sales data

12.4.1 Time lagging

Time lagging is a common problem when matching weather data and sales data. Time lagging would have been a problem if the dataset contained observations of sales to stores. Luckily, this dataset contains observations of weekly sales out of stores. Therefore the only source of time lagging here is if consumers purchase beverages prior to a hot day to prepare, or following a hot day as a reaction to a hot period that just occurred.

To check for time lagging a linear regression was used. First sales in week *t* were regressed against temperatures in week *t*. Next sales in week *t* were regressed against temperatures in week *t-1*. Finally results from the two regressions were compared to see if sales are highest correlated to temperatures in the same period or temperatures in the previous period.

Data from May till September was tested. Sales in period *t* were 80% correlated to temperatures in period *t.* Sales in period *t* were 70% correlated to temperatures in period *t*. These results imply that there is no time lag in beverage consumption, at least not when the period of measurement is weeks. Beverage sales are in this case recorded at point of sales to consumers. Therefore the logical assumption is also that there is no time lag. For that reason we will throughout the rest of this case study assume that potential time lagging problems are absent or small enough to be ignored. Consequently the dataset will not be adjusted for time lagging.

12.4.2 Adjusting for campaigns

Special offers on soft drinks are frequently seen in stores. Such special offers come from a reduced price on soft drinks from the brewery. In addition the brewery can arrange with stores to place their beverages at strategically advantageous locations in the store. Both special offers and more lucrative placement of the goods will result in increased sales. Data on the effect of campaigns were not available, therefore this factor has not been accounted for in this analysis.

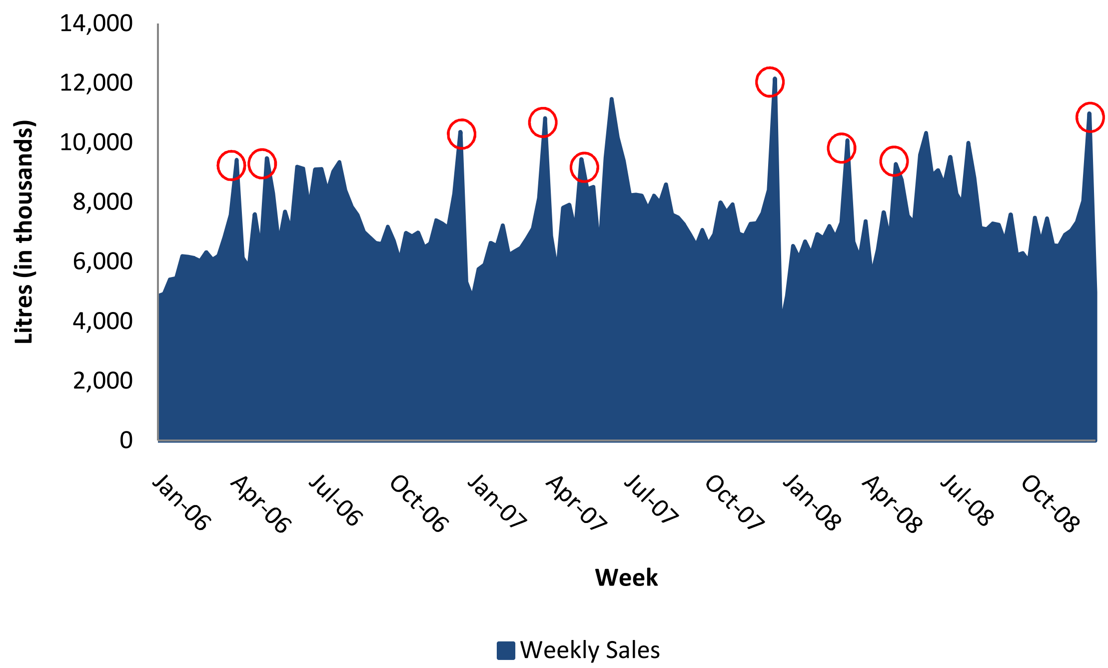
12.4.3 Adjusting for holidays

Data analysis and discussions with Morten Krogsæter, forecast manager at Ringnes, revealed that Ringnes have three periods throughout the year where sales are extremely high regardless of temperature. During Christmas, week fifty and fifty-one, during Easter holiday and on the Norwegian national day, 17th of May, Norwegians have strong traditions for consuming large amounts of beverages. These traditions will probably remain strong in the future. However, including them in the dataset will strongly underestimate the effect of temperature on beverage sales. The observations for these weeks will be replaced using the simple formula

$$Sales_t = \frac{Sales_{t-1} + Sales_{t+1}}{2} \tag{12.1}$$

The original dataset is plotted in Figure 17 to illustrate how sales for these weeks deviate from normal sales.

Figure 17 **Weekly Beverage Sales (Original dataset)**

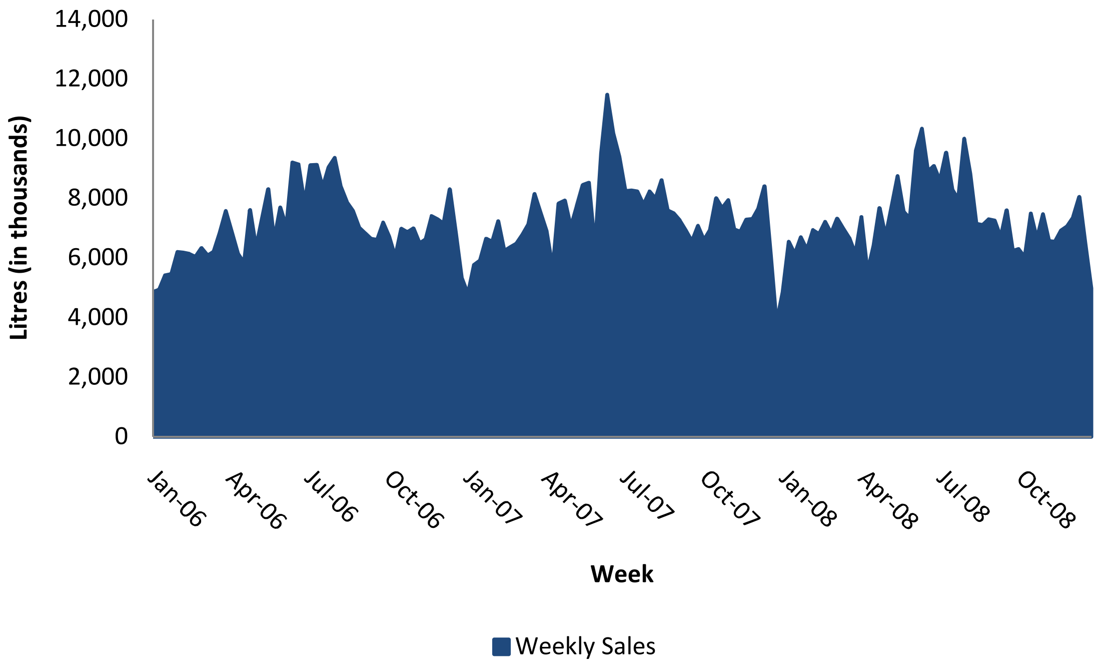


The critical eye might argue that the general staff holiday is in July and therefore July should also be adjusted for holidays. The need to adjust July sales was also a concern for the author and therefore the topic was analysed. Christmas, Easter and the National day are all short and intensive holidays. General staff holiday on the other hand last for several weeks. If the hypothesis that general staff holiday in July significantly affected beverage sales were to be true we would expect beverage sales in July to be by far the highest in the year. However, June is the month with highest monthly beverage sales.

In addition, Norwegians have strong traditions for consuming large amount of beverages on Christmas, Easter and the Norwegian national day. People consume large amounts of beverages during the general staff holiday too. Still, the general staff holiday itself is not believed to be a trigger to increased sales, as is the case with Christmas, Easter and the Norwegian national day. Therefore we conclude that there is no need to adjust the general staff holiday for holidays.

Figure 18 shows beverage sales adjusted for the three mentioned holidays Christmas, Easter and the Norwegian national day. After adjusting for the three holidays one can see a clear seasonal trend in beverage sales. Beverage sales are highest during summer, before they gradually decrease during autumn, bottom out in winter and start to increase during spring.

Figure 18 Weekly Beverage Sales (Adjusted for holidays)

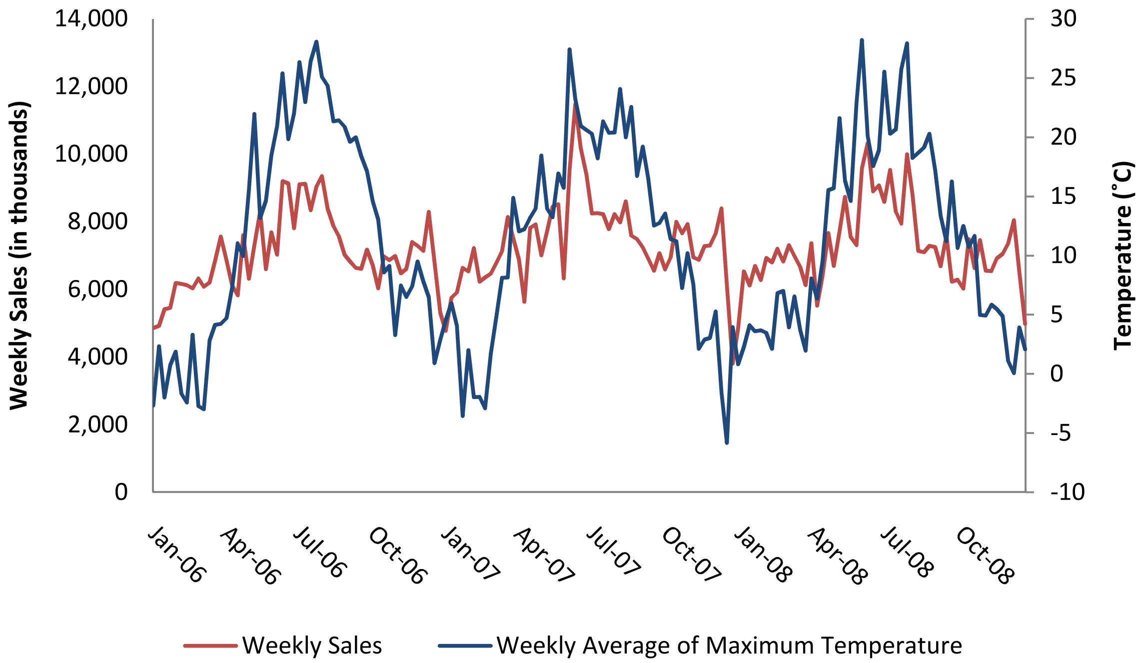


12.5 Modelling the relation between beverage sales and temperatures

The purpose of this Section is to decide which model that best describes the relation between beverage sales and temperature. The model that best describes temperature will be used to estimate the effect of one ˚C on beverage sales. This value will later be used in valuation of a weather derivative when we try to create a hedging strategy for Ringnes.

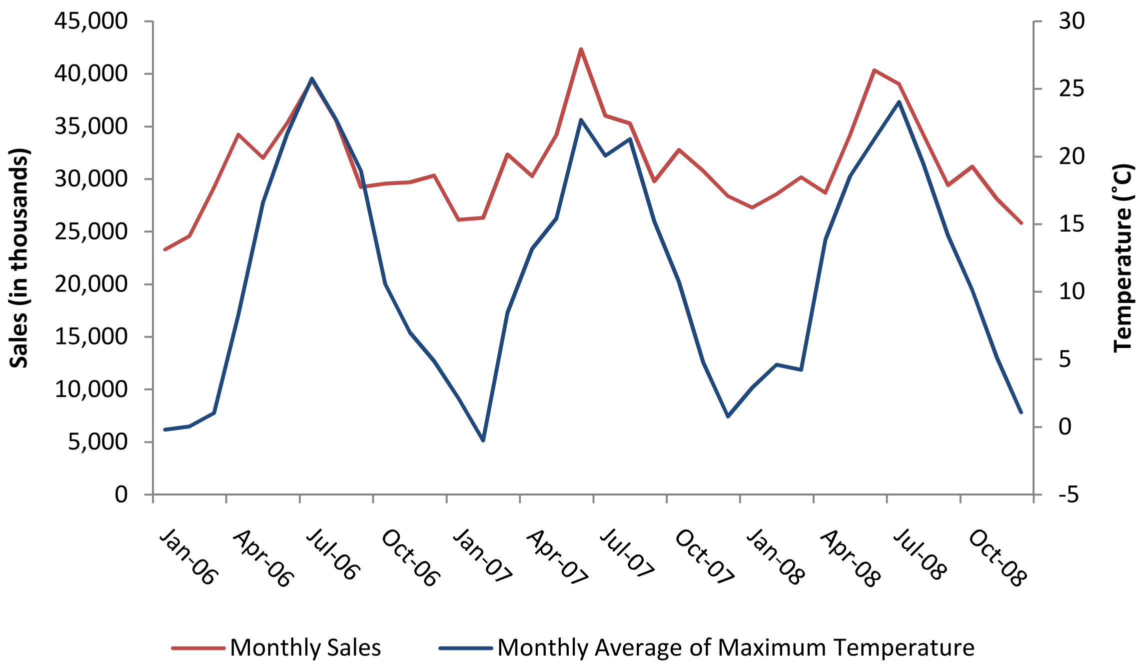
To get a rough impression of the relation between beverage sales and maximum temperatures, the two datasets are plotted against each other in Figure 19.

Figure 19 **Weekly Sales vs. Weekly Average of maximum temperatures**



From Figure 19 it is quite obvious that there is some sort of relation between beverage sales and maximum temperature. The relation seems to be strongest during the summer period. During winter periods maximum temperature declines by a greater magnitude than beverage sales. To reduce some of the noise from use of weekly data, a similar graph will be shown for monthly sales and monthly average of maximum temperatures.

Figure 20 **Monthly Sales vs. Monthly Average of maximum temperatures**



From Figure 20 we can see that the summer season from May till September is affected the most by changes in temperature. Changes in temperatures below 15 ˚C seem to have less effect on sales than changes in temperature above 15 ˚C. To implement this in a valuation model we create an index on Beverage Degree Days with a baseline of 15 ˚C, as explained in chapter 5. The only difference is that since beverages mainly are consumed during the day, we will use maximum temperatures, not average temperatures. The definition of BDDs we will use here then becomes

$$Daily\ BDDs = Max\ [(\,T_{Max} - T_{Base}), 0] \qquad (12.2)$$

The next step would optimally be to determine the effect one additional BDD have on beverage sales during the summer season. Unfortunately we only have three years of data available so running a regression on seasonal sales will be useless. However, we have fifteen summer month observations. As a an alternative approach the effect of one additional BDD on beverage sales during the summer season will be determined by running regressions on monthly beverage sales versus monthly accumulated BDDs. The effect we arrive at will later be adjusted so that it can be used to for seasonal purposes.

To analyse the relation between beverage sales and accumulated BDDs several types of regressions like linear, 2nd order polynomial, logarithmic and exponential were used. Even though a regression returns good statistical results, it doesn't necessarily mean it is the best model to use. It is also important that the results from the model can be explained by logical reasoning. The models with the best logical explanation to the relation between beverage sales and accumulated BDDs are the linear model and the exponential model. A logical explanation can also be given by the second and third order polynomial regression models, but on as few as fifteen observations these models are in danger of over fitting the model to the observations. However, the polynomial regression models would be very interesting to test on a larger dataset. Next the linear regression model and the exponential regression model will be discussed in detail.

12.5.1 Simple linear regression model

The simple linear regression model tries to predict a variable , the dependent variable, based on the value of a known variable, the independent variable. In the most commonly used formula y is the dependent variable, x is the independent variable, β_0 is the value of y when x is 0, β_1 is the slope of the line and ε is the error variable (Keller, 2006).

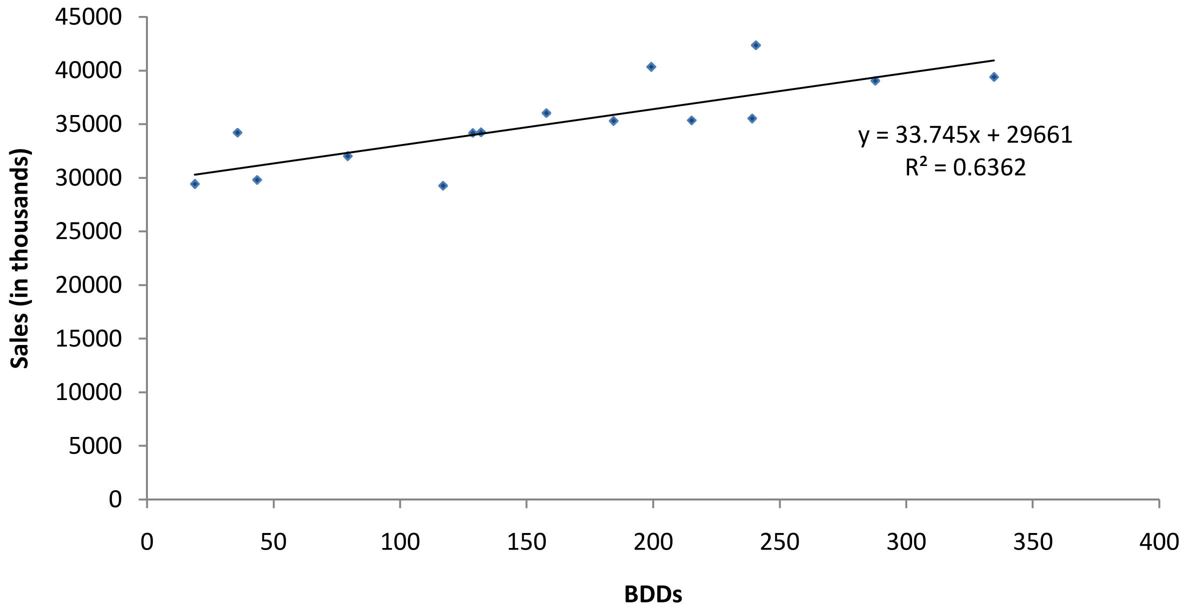
$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \qquad (12.3)$$

The logic behind this model is that there is a constant relation between beverage sales and BDDs. More specific, an increase from 200 to 201 BDDs has got just as big effect on beverage sales as an increase from 300 to 301 BDDs.

The main assumption of the model is that the relation between x and y is a straight line variable. The model also assumes that the values of the independent variable, x_t, are fixed. The only randomness in the values of the dependent variable, y_t, comes from the error term ε_t. The final big assumption is that the error terms ε_t are normally distributed with mean 0, constant variance σ^2 and that the errors are uncorrelated.

The simple linear regression model was used with monthly sales from 2006 to 2008 as the dependent variable y_t, and monthly accumulated BDDs as the independent variable x_t,

Figure 21 **Linear Regression of Monthly Sales vs. Monthly Accumulated BDDs for May - September**



The coefficient of determination, R^2, of 64%, implies that in the linear model 64% of the changes in beverage sales are explained by changes in accumulated BDDs. It also tells us that the correlation, R, between beverage sales and BDDs is as high as 80% in the summer season. Linear regression suggests that one additional BDD results in 33 745 additional litres of beverage sold. In more common terms, if all maximum temperatures in July were above 15 ˚C and increased by 1 ˚C, this would result in monthly additional sales of $31_{(BDDs)}$ $*33\ 745_{(BDDs/L)} = 1\ 046\ 095_{L}$. More general, during summer season 1 ˚C increase in temperatures roughly results in 3.4 % increase in Ringnes' beverage sales.

It is important to notice that this linear regression and the following exponential regression are on monthly data. Optimally seasonal data should be used to analyse the relation between sales and BDDs. However, we only have three years of sales data available. We may run a regression on three seasons of sale which would be close to pointless. Instead regressions are run on fifteen monthly observations, five from each of the years with sales data. β_1 from the regression will give the affect on sales for an additional BDD. We assume this affect can be directly used as β_1 also for the entire period from May till September. β_0 from the regression will give the fixed sales volume that does not depend on temperature. We assume that this fixed sales volume can be converted to a seasonal value simply by multiplying by number of months in the season.

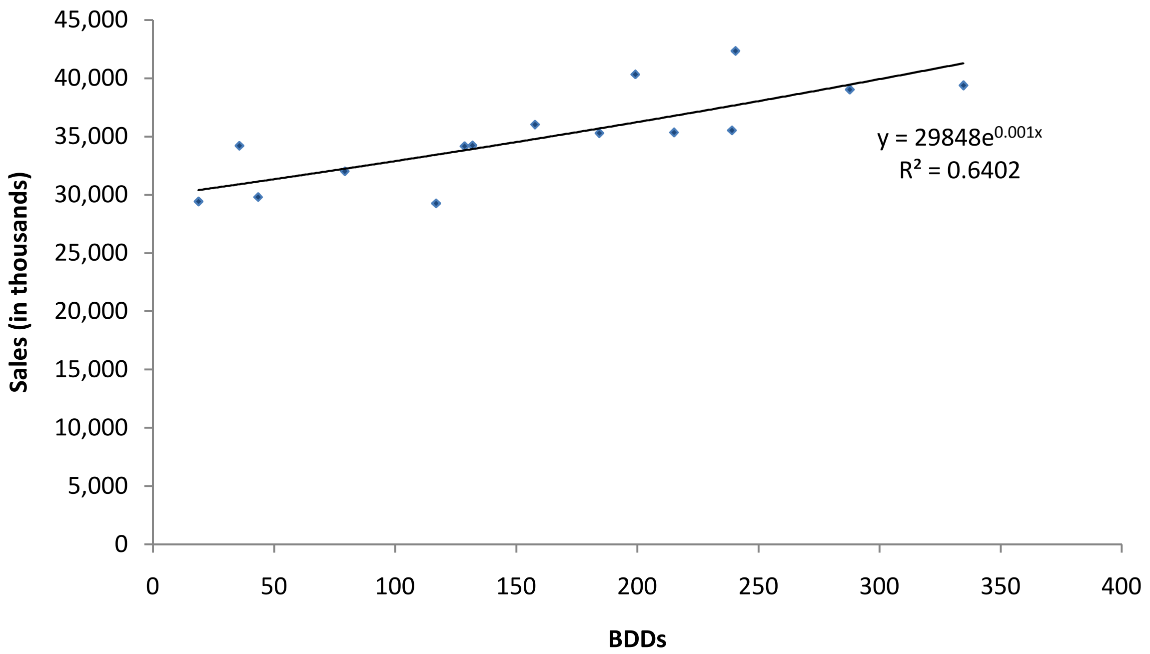
12.5.2 Exponential regression model

The exponential regression model tries to predict a variable, the dependent variable, based on the value of a known variable, the independent variable. The exponential regression model differs from the linear regression model in the way that it tries to explain the relation between the independent and the dependent variable. While the linear regression model suggests linear relation, the exponential model suggests an exponential relation where y_t increases by larger magnitude as x_t increases.

$$y_t = \beta_0 + e^{\beta_1 x_t} + \varepsilon_t \tag{12.4}$$

Applied to our data the logic behind this model is that the higher accumulated BDDs, the larger the effect of one additional BDD on beverage sales.

Figure 22 **Exponential Regression of Monthly Sales vs. Monthly Accumulated BDDs for May-September**



The coefficient of determination, R^2, of 64%, implies that in the exponential model 64% of the changes in beverage sales are explained by changes in accumulated BDDs. The correlation, R, between beverage sales and BDDs is also in the exponential model as high as 80% in the summer season.

12.5.3 Choosing the appropriate model

In both models analysed monthly accumulated BDDs explain approximately 64% of the changes in monthly beverage sales. However, the chosen model will be used on seasonal accumulated BDDs. An index of seasonal accumulated BDDs will have much higher values than an index of monthly BDDs, hence the effect on sales will be vastly overestimated by the exponential model. Ringnes' market intelligence indicates that especially water sales have an exponential growth at high temperatures. However, Ringnes' market intelligence also indicates that for high temperatures there is a shift in beverage consumption from beer and soft drinks to water. Hence, it seems reasonable to assume a linear relation for total beverage sales.

13 HEDGING STRATEGIES

Chapter 12 revealed that there is a strong positive correlation between temperature and Ringnes' beverage sales. As a consequence Ringnes is exposed to weather risk. From Figure 19 and Figure 20 it is evident that the consumption of Ringnes' beverages in highest during the summer season. A warmer than normal summer could boost their sales and gross profits, while a colder than normal summer could reduce sales and gross profits, and even put the company or a particular group of product under distress.

Before we analyse the potential use of weather risk management tools, we should check for natural hedging. Ringnes sales are spread throughout Norway. If low temperatures in Oslo are positively correlated with high temperatures in other Norwegian cities Ringnes gross profits would to some degree be naturally hedged. Reduced sales in Oslo would be compensated by increased sales in other cities. For that reason it is important to check the correlation of temperature in Oslo to temperatures in other Norwegian cities.

Table 4 Correlation Matrix of May–September Daily Maximum Temperatures for a Geographically Dispersed Sample of Norwegian Cities

	Oslo	Kristiansand	Stavanger	Bergen	Trondheim	Tromsø
Oslo	100%	96%	91%	90%	86%	80%
Kristiansand	96%	100%	92%	90%	85%	79%
Stavanger	91%	92%	100%	97%	88%	78%
Bergen	90%	90%	97%	100%	90%	78%
Trondheim	86%	85%	90%	90%	100%	86%
Tromsø	80%	79%	78%	78%	86%	100%

From Table 4 we can see that not surprisingly temperatures in Norwegian cities are closely correlated. For Ringnes closely correlated temperatures imply above average total gross profits during hot summers and below average gross profits during cool summers. We can therefore conclude that Ringnes' beverage sales are not naturally hedged.

To secure stable gross profits Ringnes should explore the company's possibilities to hedge volumetric risk by use of weather derivatives. Ringnes' weather risk is largest during the summer season. Hence a possible hedging strategy should be created for the summer season. The company can choose between daily, weekly, monthly and seasonal contracts. Long contracts have smaller standard deviations. Hence a seasonal contract is relatively cheaper than five monthly contracts. We want to analyse a possible hedging strategy for the summer season from May till September. Therefore we choose to analyse a seasonal contract on the period May till September. Possible hedging strategies include use of futures, swaps and options.

Ringnes portfolio of beverages mainly consists of soft drinks, beer and water. Roughly Ringnes' gross profits from one litre sold are 7 NOK for beer, 7 NOK for water and 6 NOK for soft drinks. Soft drinks account for approximately 45% of Ringnes sales. As a rough estimation we will assume Ringnes' have 6.5 NOK in gross profits per litre of beverage sold.

Change in gross profit is calculated by multiplying change in sales by the average gross profit for one litre of beverage

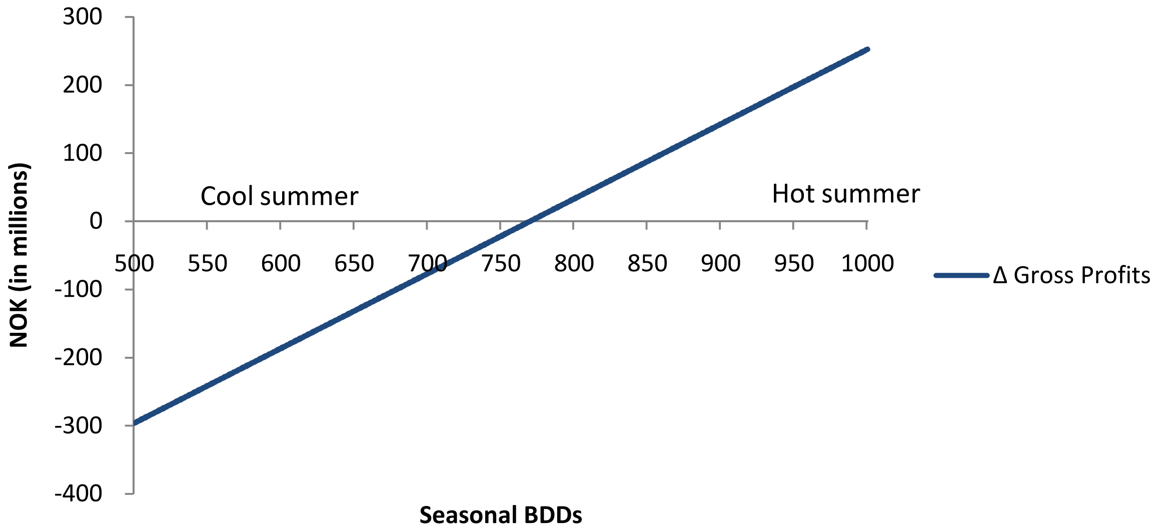
$$\Delta\, Gross\ Profit_{Total} = \Delta Sales_{Total} * \overline{Gross\ Profit_{L}} \tag{13.1}$$

Based on this estimate the regression from Figure 21 gives a change in gross profit per BDD of

$$\Delta\, Gross\ Profit = 33\,745_{L} * 6.5_{NOK/L} = 219\,342.5\ NOK \tag{13.2}$$

The ten year average for seasonal BDDs is 770 BDDs, the minimum is 603 BDDS and the maximum is 985 BDDS. Seasonal BDDs above this level result in higher than normal sales, while seasonal BDDs below this level result in lower than normal sales. Ringnes' exposure to weather risk during the summer season is summarized in Figure 23. Figure 24, Figure 25 and Figure 26 all assume the linear relation between beverage sales and seasonal BDDs from Figure 21 holds.

Figure 23 **Deviation from Normal Gross profits during Summer Season**



To hedge their exposure to weather risk Ringnes may apply several risk management tools. Futures, put options and collars will be discussed here.

13.1 Short futures

Ringnes' weather risk could be hedged by a short future contract on seasonal BDDs. The payoff from a short future contract at maturity is

$$Payoff\ Short\ Future = F_0 - S_T \tag{13.3}$$

where F_0 is the original future price and S_T is the spot price at maturity. Futures are originally used for commodities. By use of the seasonal BDD-index weather is commodified, and future contracts on weather can be traded.

Payoff on the short future is illustrated in Figure 24. F_0 is set to 770 BDDs, the 10-year average. A tick-size of 10 000 NOK is used for all derivatives. Number of short future contracts is decided by

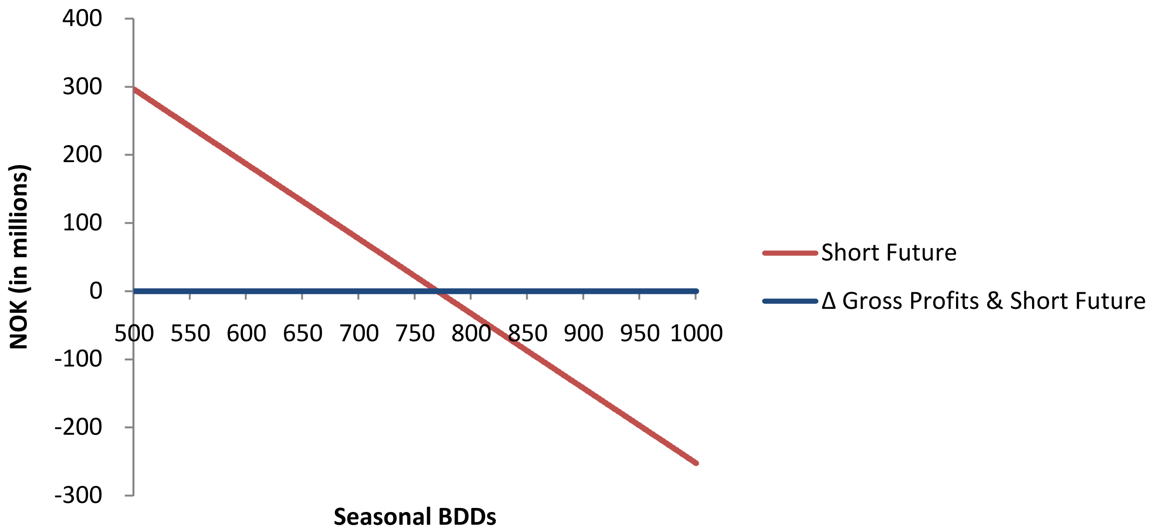
$$Number\ of\ Contracts = \frac{\Delta\, Gross\ Profit}{\Delta\, Short\ Future} \tag{13.4}$$

by entering our numbers into this equation we get

$$Number\ of\ contracts = \frac{219\ 342.5}{10\ 000} = 21.93425 \tag{13.5}$$

To fully hedge our portfolio we need to short 21.93425 future contracts. As all tick-sizes are set to 10 000 NOK, this is also the number of contracts needed in the other hedging strategies.

Figure 24 Payoff at Maturity for Short Futures on Seasonal BDDs



A strategy with a short future would give up the entire upside from a hotter than normal summer. Even though a future is costless to buy, giving away the entire upside is not something Ringnes would want to do. Hence a hedging strategy to short futures will not be chosen.

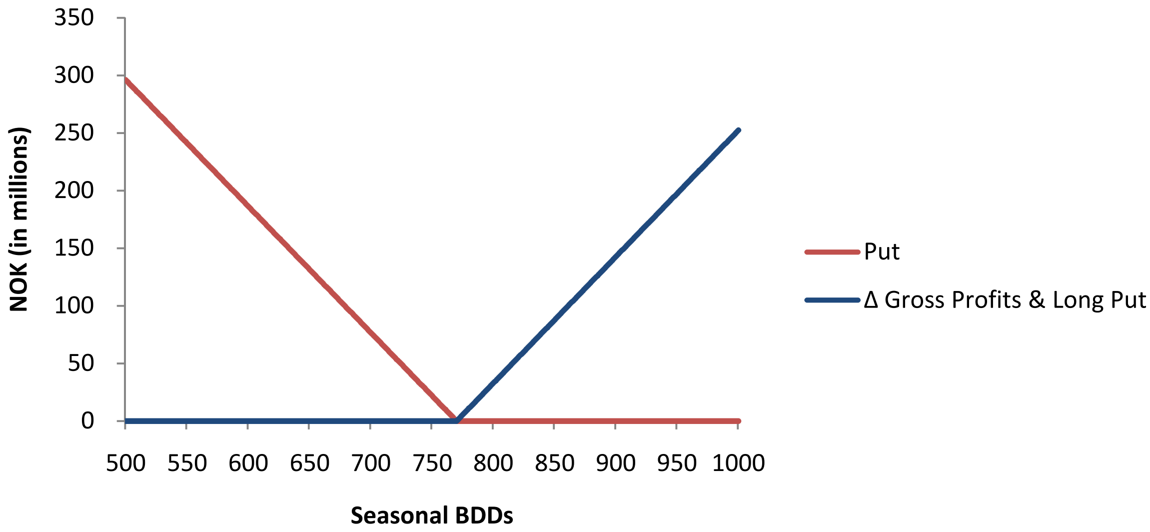
13.2 Put option

Ringnes' weather risk could be hedged by a put option on seasonal BDDs. The payoff from a put option at maturity is

$$Payoff\ Long\ Put = Max(K - S_T, 0) \tag{13.6}$$

where K is the strike and S_T is the index-value at maturity. For this example the strike K is set 770 BDDs, the 10-year average. 21.93425 put options with tick-size of 10 000 NOK, and a strike of 770 BDDs gives the payoff-profile in Figure 25. In reality one cannot buy half contracts. Still, as the tick-size may vary, the number of contracts needed to hedge is presented with all decimals. For example, 21.93425 put options with a tick-size of 10 000 NOK is practically the same as 2 193 425 put options with a tick-size of 0.1 NOK.

Figure 25 Payoff at maturity for Put Options on Seasonal BDDs



Put options on seasonal BDDs give a positive payoff for cold summers. For hot summers, summers with seasonal BDDs above average, put options give zero payoff. In contrast to the strategy to short futures, the strategy to buy put options do not give away upside from a hotter than normal summer. However, this comes at a cost since Ringnes would have to pay an option premium for the puts. However, we can reduce the option premium since the put option price will decrease as the strike, K, is decreased. This is simply a choice between how much we are willing to pay for a put option, and how much of the downside risk we want to hedge. If the option premium is not too high, a hedging strategy with long put options would be a very interesting to implement.

13.3 Collar

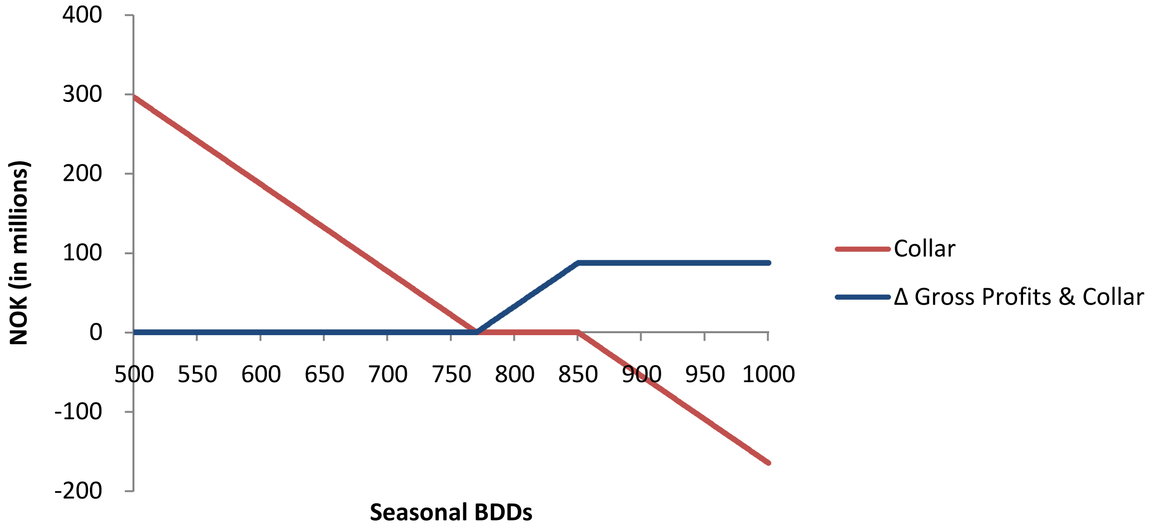
To reduce the option premium from the put option strategy Ringnes could choose to give away some of their upside. This could be done by a combined strategy of long puts and short calls, also called a collar. The payoff from the collar strategy is

$$Payoff\ Collar = Payoff(Put) - Payoff(Call) \qquad (13.7)$$

$$Payoff\ Collar = Max(K_P - S_T, 0) - Max(S_T - K_C, 0) \qquad (13.8)$$

where K_P, is the strike attached to the long put, and K_C is the strike attached to the short call. K_P is set to 770 BDDs and K_C is set to 850 BDDs.

Figure 26 Payoff at Maturity for Collars on Seasonal BDDs



A collar strategy will reduce the risk of a cool summer just as much as a strategy of long put options. However, a collar strategy is cheaper than a strategy purely based on put options. A collar strategy is cheaper because it gives away all upside above K_C by shorting call options. Also here we have a trade-off between low option premiums and risk. Option premiums can be reduced by lowering the strike of the long put option or by increasing the strike of the short call option. This trade-off allows us to adjust the option premium and risk level very well, which makes the collar strategy an interesting strategy to Ringnes. However, to limit the case, we will here assume that Ringnes want to retain the upside potential and therefore choose the long put strategy to hedge their weather risk during the summer season.

14 APPLIED WEATHER DERIVATIVE VALUATION

In this Section we will perform valuation of the instrument chosen to be the most appropriate in a hedging strategy. The most appropriate hedging strategy in Ringnes' case is a long put option on seasonal accumulated BDDs. The long put option will be valued by use of historical burn analysis, distribution analysis and a dynamical model.

14.1 Historical burn analysis

The first step in a historical burn analysis is to decide how many years of data to use. To see if this choice will make a big difference we plot the average May-September accumulated BDD-index for all averages from fifty to one year.

Figure 27 **Historical Average and Standard Deviation for May-September BDD-index**

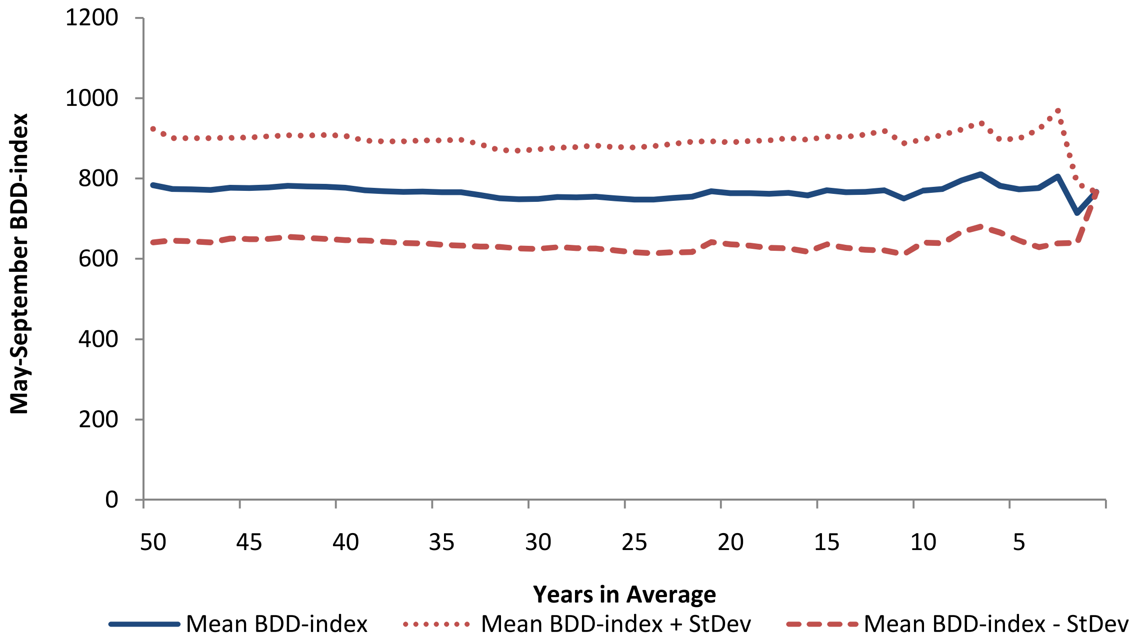


Figure 27 shows that the historical average of May-September BDD-indexes is fairly stable. This is as expected since we have de-trended historical weather data. Recent weather data is a better indicator of future weather than fifty year old weather data. Therefore the historical burn analysis is performed on the 10-year average of accumulated May-September BDD-indexes. Summary statistics are listed in Table 5.

Table 5 Summary statistics of the 10-year average May-September accumulated BDD-index

Average	**770**
SD	128
SD (%)	17 %
Max	810
Min	714

We assume Ringnes is willing to accept some downside risk. Therefore the strike of the long put option is set slightly below 10-year average at 750 BDDs. In chapter 13 we arrived at a change in Ringnes' gross profits of 219 342.5 NOK for a change of one BDD. As the tick-size is set to 10 000 NOK, we will need 21.93425 contracts.

We have chosen a strike, we know the tick value and we know how many contracts we need. Now we can calculate the fair premium of a put option on seasonal accumulated BDDs for the period from May till September. This will firstly be done by use of historical burn analysis as described in Section 9.3.

Table 6 **Data from Historical Burn Analysis**

Year	May-Sep BDD-index	Payoff
1999	748	NOK 172 235
2000	634	NOK 1 468 405
2001	699	NOK 591 912
2002	991	NOK 0
2003	849	NOK 0
2004	769	NOK 0
2005	700	NOK 604 199
2006	991	NOK 0
2007	699	NOK 883 956
2008	782	NOK 0
Mean	786	NOK 372 071
Standard Deviation	123	NOK 505 339

The risk neutral, undiscounted price of the option is 372 071 NOK. At this price both the buyer and the seller would have gone break-even in the long run. As we can see standard deviation of the payout is extremely high, at 136%. This is a result of large fluctuations in payoff. A traded option will deviate from the risk neutral price for two reasons. The risk neutral price does not account for the time difference of the cash flows. An option premium is in this case paid at least five months earlier than a potential payoff. To account for this time difference we need to discount the fair price by the risk free rate, r_f. In addition, a seller of a put option takes on risk. The seller will require compensation for bearing risk. As compensation he will require a risk premium.

If the seller uses a risk premium of 10% the price of one put option would be

$$372\,071\ NOK + 3\,72\,071\ NOK * 10\% = 409\,278\ NOK \tag{14.1}$$

For simplicity let's assume t_0 is 1st of January 2009. Maturity T of the contract is 30th of September 2009. If the provider of the long put option uses this historical burn analysis asking price will be

$$Long\ Put\ Option\ Premium_{Offer} = [E(P) + R(P)] * e^{-r_f * T} \tag{14.2}$$

where

r_f is the risk free rate, and T is time to maturity. Time to maturity is nine months, hence we assume Norwegian 9-month Treasury Bills can be used as risk free rate. In January

2009 the Norwegian 9-month Treasury Bill-rate was 2.23% (Norges Bank, 2009). This gives

$$Long\ Put\ Option\ Premium_{Offer} = [409\ 278\ NOK] * e^{-0,0223*(9/12)} = 402\ 489\ NOK \tag{14.3}$$

By use of historical burn analysis the option premium required from a market-maker based on the last ten years is 402 489 NOK. It is worth noticing that the standard deviation of this historical burn analysis is very high. This is partly because we only have ten observations, and partly because standard deviations of options almost are high by definition. The minimum payout is zero and they are common. The maximum payout is infinite. Payouts of zero reduce the average by a considerable amount, while large payouts like the ones in 2007 and 2000 contribute to a very large standard deviation. If the market-maker required a risk premium based on standard deviation of historical payouts, the risk premium, and thereby the offered option premium would be substantially higher.

By varying the number of years used in the analysis from ten to fifty the price offered by the market maker varies from 370 000 NOK to 570 000 NOK. Historical burn analysis is useful for quickly getting a rough estimate for the option price. We can see that historical burn analysis quite limited in its accuracy. Hence the analysis should only be used in combinations with other models, as a rough estimate on the option price.

14.2 Distribution analysis

A more accurate weather derivative valuation method is distribution analysis. We can gain much in our analysis with a better understanding of the statistical properties of the underlying index. Without knowing the probability distribution we are limited to the available amount of historical weather data. If we can determine the probability distribution of the May-September accumulated BDD-index, we can use historical data to decide the index's mean and standard deviation. In cases where we can determine an index's probability distribution, price accuracy can be greatly improved, as knowing the probability distribution allows us to run a very large number of simulations to estimate the average payout.

We use fifty years of data to determine the probability distribution of the accumulated May-September BDD-index. As only fifty years of data is used we will not get a perfect match with any statistical distribution. However, we will get a good idea of which distributions that approximately fit the BDD-index.

Figure 28 Probability Density Function for the Accumulated May-September BDD-index

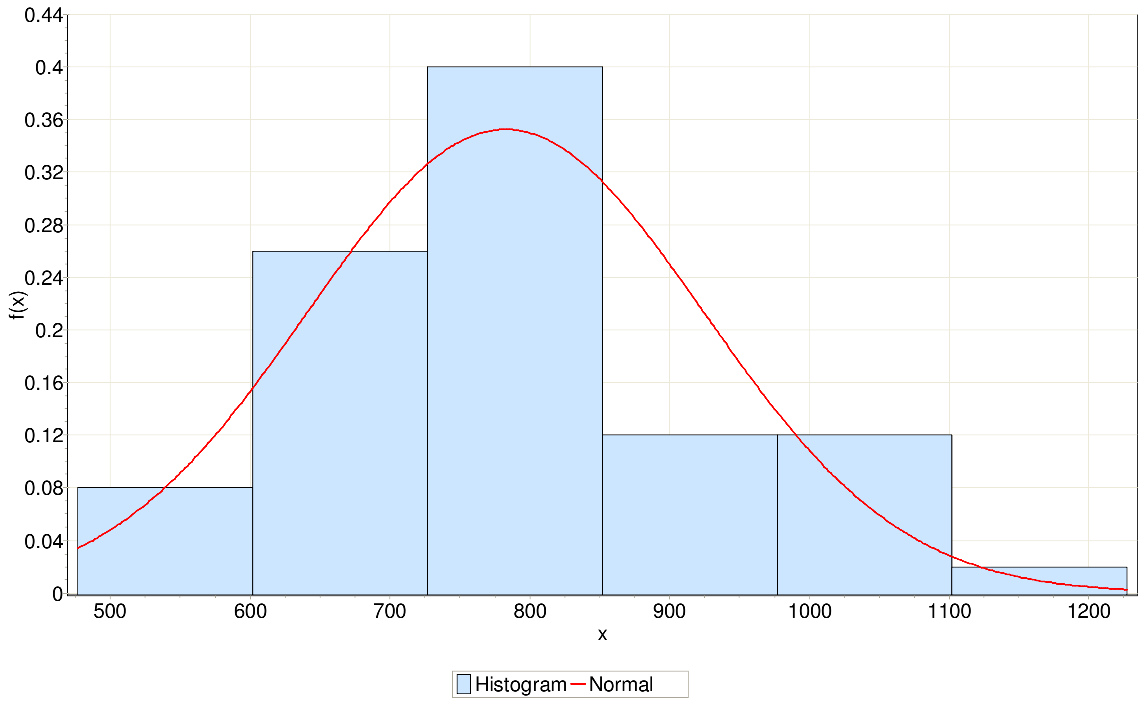


Figure 28 shows a histogram of observed values for the BDD-index during the last fifty years. We have relatively few observations, so the histogram is not smooth as the normal distribution. Still, we can see obvious similarities between the normal distributions and the distribution of BDD-index observations.

14.2.1 Goodness-of-fit test

To get a better idea if the normal distribution can be applied to the accumulated May-September BDD-index we use a statistical goodness-of-fit test. The goodness-of-fit test used is the Chi-Squared test (D'Agostino & Stephens, 1986).

The Chi-Squared test is applied to binned data, so the value of the test statistic depends on how the data is binned. The Chi-Squared statistic is defined as

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{14.4}$$

where O_i is the observed frequency for bin i, and E_i is the expected frequency for bin i calculated by

$$E_i = F(x_2) - F(x_1) \tag{14.5}$$

Where F is the cumulative distribution function of the probability distribution being tested, and x_1 and x_2 are the limits for bin i.

The null hypothesis that the data follows the specified distribution is rejected at the chosen significance level α if the test statistic is greater than the critical value defined as

$$\chi^2 1 - \alpha, k - 1 \tag{14.6}$$

where k is the number of bins.

Table 7 Goodness-of-Fit Statistics for the Accumulated May-September BDD-index

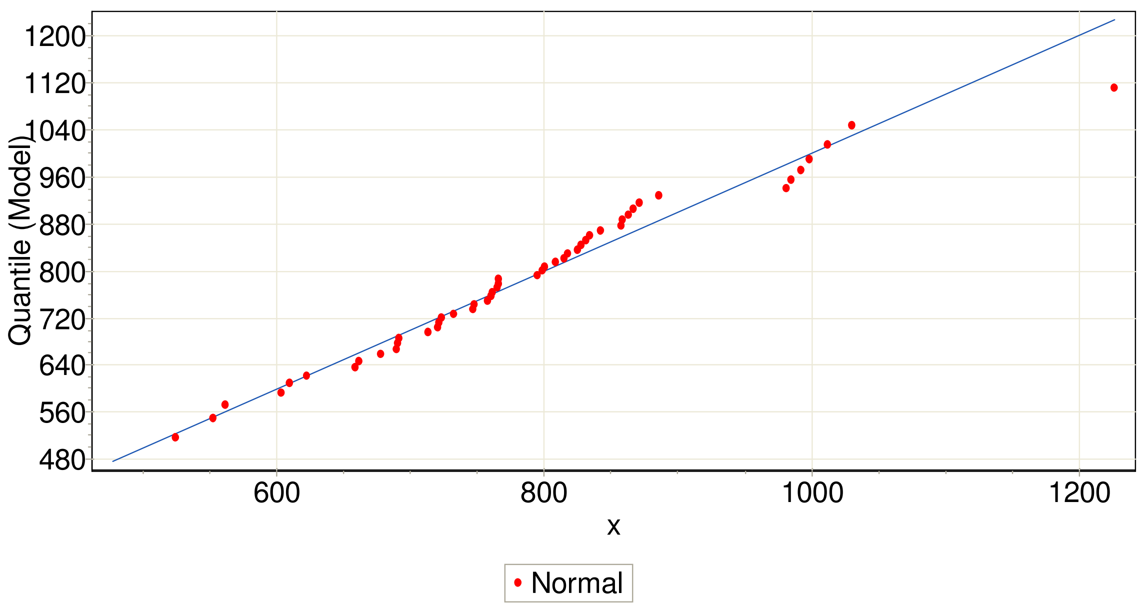
Deg. of Freedom	5				
Statistic	2.639				
P-value	0.755				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	7.29	9.24	11.07	13.39	15.09
Reject?	*No*	*No*	*No*	*No*	*No*

The null hypothesis is that normal distribution can be applied to the BDD-index. The Chi-Squared test does not reject the null hypothesis. The test shows a P-value of 0.755.

This means there is a 76% chance of observing a test statistic at least as extreme as the one computed.

Further, the observed data is plotted in a Quantile-Quantile plot to see if the data is normally distributed. If the accumulated May-September BDD-index is normally distributed we would expect to see the historical observations, in the graph marked by red dots, follow the blue line which represents the normal distribution. The Quantile-Quantile plot in Figure 29 shows that historically observed values for the BDD-index follows the line representing normal distribution, indicating that the BDD-index is normally distributed.

Figure 29 Quantile-Quantile Plot of the accumulated May-September BDD-index against the Normal Distribution



Finally we will test the skewness and kurtosis of the dataset. Skewness is a measure of symmetry, or more specific a lack of symmetry. The normal distribution has a skewness of zero, and any symmetric data should have skewness close to zero. A negative skewness value indicates that the dataset is slightly skewed to the left, while a positive skewness indicates that the dataset is slightly skewed to the right. Our dataset shows a skewness of 0.47, which is not far from zero. A skewness of 0.47 indicates that the dataset is slightly skewed to the right. This might sound strange by looking at Figure 28, but most observations in the mid-column of the histogram are actually to the right of the mean.

Kurtosis is a measurement of whether the data are flat or peaked relative to the normal distribution. The normal distribution has a kurtosis of zero. A positive kurtosis indicates that the data peak near the mean, while a negative kurtosis indicates that the distribution of observations is relatively flat. Our dataset has a slightly positive kurtosis of 1.12 indicating that the data peak near the mean. However, this is not very far from the normal distributions kurtosis of zero.

Based on results from the Chi-Squared test, Q-Q plotting, and test of skewness and kurtosis we conclude that there is little or no reason not to use the normal distribution for our dataset on May-September accumulated BDD-indexes for Oslo. This is also supported by former studies of May-September accumulated BDD-indexes on several US cities (Jewson, Weather Derivative Pricing and the Distributions of Standard Weather Indices on US temperatures, 2004).

Now that we have determined the distribution of our dataset we can use the dataset for simulations on what the May-September accumulated BDD-index value will be for the next period.

A Monte Carlo Simulation was used to simulate 10 000 outcomes of the May-September Accumulated BDD-index. The outcomes are summarized in Table 1Table 8.

Table 8 **Summary statistics for Simulations of the May-September accumulated BDD-index**

Average	**783**
SD	141
SD (%)	18 %
Max	1298
Min	226

The following formula was used in the simulations

$$Payoff = Max(K - S_T, 0) * \text{Tick-size} \qquad (14.7)$$

where

$K = 750$

$S_T = \mu + \sigma\varepsilon = 782.73 + 140.97\varepsilon$

Tick-size= 10 000 NOK

Table 9 **Summary statistics for Payoffs from a Put Option on simulated May-September Accumulated BDD-indexes**

Average	**NOK 415 447**
SD	NOK 713 420
SD(%)	172%
Max	NOK 5,238,454
Min	NOK 0

Table 9 shows the statistical results from the simulations. The risk neutral, undiscounted, price of a put option on the May-September Accumulated BDD-index for Oslo is 415 447 NOK.

To arrive at the option premium at which the market-maker is willing to sell a put to Ringnes we add a risk premium of 10% and discount the cash flows by the Norwegian 9-month Treasury Bill-rate.

$$Long\ Put\ Option\ Premium_{Offer} = [415\ 447\ NOK + 415\ 447 * 10\%] * e^{-0{,}0223*(9/12)} = 449\ 412\ NOK$$

The price we can buy the put option for from a risk-averse provider is 449 412 NOK.

14.3 Dynamical model

Among the more common weather derivative valuation methods dynamical models are probably the most realistic models, but they are also the most advanced. To apply a dynamical path-depending valuation model we need to simulate future daily maximum temperatures. The simulation method used is based on Dischel's D1 Stochastic Temperature Model for Valuing Weather Futures and Options.

$$T_{t+1} = \alpha\Theta_{t+1} + \beta T_t + \gamma\Delta T_{t,t+1} \tag{14.8}$$

Regression on historical temperatures from 1999 to 2008 gave the constant values

$\alpha = 0.22$

$\beta = 0.78$

$\gamma = 0.95$

The temperature for 1.January was then calculated as

$$T_{1.Jan} = 0.22 * \overline{T\ 10 - year}_{1.Jan} + 0.78 * T_{31.Dec} + 0.95 * \Delta T_{31.Dec,1.Jan} \tag{14.9}$$

Based on this model the next day's temperature is 22% decided by the 10-year average temperature for that specific date and 78% decided by previous day's temperature. In addition a random term with expectation zero affects the next day's temperature.

The dynamical temperature model was used to simulate 1000 outcomes for each day's maximum temperature in 2009. Based on the sample of outcomes we could derive 1000 outcomes for the May-September accumulated BDD-index. Finally from the 1000 outcomes of the BDD-index we could calculate 1000 option payoffs. The average option payoff is used as the expected payoff in further valuation of a put option on the May-September accumulated BDD-index.

Table 10 **Summary statistics for Simulation of Put Option on the May-September Accumulated BDD-index**

Average	**NOK 415 179**
SD	NOK 712 568
SD (%)	171.63 %
Max	NOK 4,836,325
Min	NOK 0

These summary statistics are very similar to the summary statistics from the distribution analysis in Table 9. As a result the option prices will not differ much. Again a risk premium of 10% is added, and the cash flows are discounted by the Norwegian 9-month Treasury Bill-rate of 2.23%.

$$Long\ Put\ Option\ Premium_{Offer} =$$

$$[415\ 179\ NOK + 415\ 179 * 10\%] * e^{-0{,}0223*(9/12)} = \ 449\ 122\ NOK \qquad (14.10)$$

By use of a dynamical model a provider would offer Ringnes to buy a long put option at 449 1 22 NOK.

15 Evaluation of the hedging strategy

We have now priced a long put option on the May-September accumulated BDD-index. To see what a hedging strategy would cost we simply multiply the option value by the number of contracts needed, in this case 21.93425.

Optimally we would now have tested our hedging strategy on real sales data. Unfortunately only three years of sales data are available from Ringnes. We could also apply the hedging strategy to sales data for another brewery, but again we don't have access to such data. An alternative method would be to simulate future sales based on the data we have. However, by simulating future sales based on the same data we have used to create our hedging strategy our strategy is destined to work well.

Instead, to get a relative understanding of how much this hedging strategy costs we calculate the price of the hedging strategy as a percent of the implicit 10-year average seasonal gross profit. The implicit 10-year average seasonal gross profits are calculated by applying the linear regression from Figure 21 to de-trended historical values of the May-September accumulated BDD-index. This approach is of course just an approximation, but it will give us a fair idea of how much of the gross profit Ringnes will have to give up to implement the hedging strategy.

Table 11 Cost of a Long Put Hedging Strategy for Total Sales

	HBA	Distribution Analysis	Dynamical Model
Long Put Option	NOK 402 489	NOK 449 412	NOK 449 122
Contracts needed	21.93425	21.93425	21.93425
Price of Hedging Strategy	NOK 8,828,302	NOK 9,857,524	NOK 9,851,151
10yr-Average Seasonal Gr. Profit	NOK 68,893,725		
Strategy Price in % of Gr. Profit	5.23%	5.84%	5.83%
ΔGr. Profit worst case 10yr	-13.77%		

Further, another rough approximation was made to calculate how big the cutback in gross profit would have been in the worst case the last ten years. The linear regression from Figure 21 was applied to de-trended historical values of the May-September accumulated BDD-index. The lowest level the last ten years was 634 BDDs during the summer of 2000. Assuming the relation from the linear regression holds, and ignoring price fluctuations, we get an estimate of 13.77% cutbacks in gross profit. While Ringnes would have benefited from hedging the weather in 2000, paying close to 6% of gross profits each summer season seems expensive. To reduce hedging costs Ringnes could consider hedging parts of their portfolio. Some beverage categories are more weather sensitive than others. Hedging the most weather sensitive beverages is more effective than hedging all beverages based on the sensitivity of total beverage sales to weather.

As we have seen before total beverage sales have an 80% correlation with BDDs. Table 12 shows that soft drinks are less correlated to BDDs than beer and water. Water on the other hand is the most sensitive to BDDs. From the coefficient of determination we can see that BDDs explain as much as 70% of the changes in water sales. For soft drinks the coefficient of determination is as low as 58%.

Table 12 Correlation Matrix of Monthly BDDs and Beverage Categories

	Correlation (R)	Coefficient of Determination (R^2)
	BDDs	
Total Sales	80%	64%
Beer	80%	64%
Water	84%	70%
Soft Drinks	76%	58%

We could increase the efficiency of our hedge by excluding the least temperature sensitive beverage, soft drinks, from our hedging strategy. However, campaigns are not accounted for in this analysis. Most campaigns are related to soft drinks as campaigns on beer are illegal in Norway. Therefore soft drinks are not necessarily the least correlated to temperature, but to get an answer to that we would need campaign data. A more extreme version would be to only hedge water sales as they are the most temperature sensitive. As we can see from Table 12 water sales are most closely correlated with seasonal BDDs. Therefore a hedging strategy which only included water sales would have a lower basis risk than a hedging strategy for total sales. Still, to limit the frames of this study the alternative to hedge only the water sales in the portfolio will not be analysed any further.

16 Conclusive remarks on use of weather derivatives in Ringnes

Analyses of Ringnes' beverage sales show strong correlations between sales and temperature. High correlation is especially the case during the summer season. Ringnes are clearly exposed to weather risk as sales in all categories tend to drop at low temperatures. To investigate the potential use of weather derivatives in Ringnes a long put option was chosen as the most appropriate hedging strategy. A long put option reduces downside risk without giving away a potential upside. Both distribution analysis and dynamical modelling arrived at a price of approximately 9.9 million NOK to hedge away downside risk.

Even with a full hedge, the basis risk would be significant as beverage sales and temperature are not perfectly correlated. When we add the high risk premiums charged by providers of weather derivatives a hedging strategy becomes expensive. A 10% risk premium roughly represents a 10% average loss on the hedging strategy. To defend implementation of such a hedging strategy we would need solid benefits in terms of reduced risk. Further Ringnes should be in a position where there is a strong need to hedge their gross profits to really consider a long put hedging strategy. Ringnes is a subsidiary of the Carlsberg Group. Carlsberg currently have a credit rating of BBB-,and outlooks are stable (Carlsberg, 2006). Hence there is room for improvement in terms of credit rating. Nonetheless, in this case the hedging strategy seems a bit expensive. The recommendation to Ringnes is therefore to leave the beverage sales in the summer unhedged. This conclusion remains till one of the following occurs.

More historical data on beverage sales are made available, and data on campaigns are made available. Better data would remove much uncertainty from our analyses and put us in a better position when the decision to hedge or not were to be made.

The second event that could alter the conclusion is a worsened financial situation in Ringnes or Carlsberg. If Ringnes could not bear a cool summer with low beverage sales it is quite obvious that they ought to give away some of the upside potential to hedge the downside risk. Nonetheless, for now the recommendation to Ringnes is to leave their summer season beverage sales unhedged.

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