# Weather Derivative
# A Tool for Risk Management in the New Millennium

**Abhijit Dutta**
Faculty Member (Finance),
The Icfai Business School,
Bhubaneswar.

**The article deals with the structure, pricing and usage of weather derivative. The weather vagaries have led to a great amount of losses for weather-reliant industries such as power, hospitality, etc. The article shows how weather derivatives can be used to tone down the losses and hedge the financial risk of industries which are directly affected by weather forces.**

There are a number of businesses in the world whose output depends directly on certain meteorological conditions.

Who can deny the fact that agriculture in India is directly dependent on the monsoon? Or for that matter, the generation of hydroelectric power across the globe is affected by rain in the catchment areas of the river.

So, what are weather derivatives? They are contracts between two parties that stipulate how payment will be executed between them depending on certain meteorological conditions during the contract period.

Weather derivatives have no relation with the financial market. Unlike a financial derivative which has an underlying asset such as stock, price, index, a weather derivative is based on weather data collected over a long frame of time.

Unlike normal commodity futures, which are derived from spot and physical markets, weather derivativation does not have either a spot or physical market. Business which is highly dependent on weather and is multilocational in nature uses weather derivatives as a risk management tool.

A weather derivative is not the same as weather insurance. To be entitled for a claim, a policy-holder must have incurred a loss and should be able to prove the same to the insurer. However, the derivative instrument is enforceable on the occurrence of an event whether or not the loss has been incurred. One might remember here that an insurance product is vague by definition of the events and are bilateral in nature whereas a derived instrument is quite concrete in definition and may be bilateral on exchange-traded. The only resemblance between the two perhaps is that both of them protect a downward risk.

The present paper is divided into three parts:

- Introduction to weather derivatives
- The pricing mechanism
- Cases on usage of weather derivatives.

## Why Weather Derivatives?

Weather risk is unique in nature. It is volume-related in the sense that weather has more to do with yield changes/losses and volume than price changes.

A cooler summer in a free market condition means lesser demand for poorer plus higher tariff for an individual. All this might actually reduce the profitability of the company.

Since, weather derivatives are not based on spot or physical market it does not suffer from basis risk. The price is, therefore, either decided bilaterally or is based on supply and demand.

Till recently, weather derivatives were not much heard of since utility sectors were mostly state-owned where profit was not a major issue. Following deregulation, it has become more important for the utility companies to manage risks arising from weather-related uncertainties.

## How are Weather Derivatives Contract Constructed?

All weather derivatives are initiated by a buyer and a seller. Both the parties mutually agree on a contract period and weather index that serve as the basis of transaction. The contract is formulated by specifying the following parameters:

- Contract type, i.e., whether put or call will be used.
- Contract period, say, October to May or May to September.
- Official meteorological record which will form the basis of the details of the contract.
- Definition of weather index which will be underlying the contract.
- Strike (S) indicating the threshold weather parameter (rain, heat, etc.).
- Tick (T) which can be an agreed payment for a given change/variation in rainfall. In case of heat contract, the tick changes for a particular degree of temperature at which the strike will be executed on level rainfall at which the tick will change per millimeter of rain. Or in other words, the contract Po for linear or binary payment schemes.

**Table 1: Risk Pattern and Weather Module Which Bring Such Risk**

| Sl. No | Type of Business | Risk Factor | Index to Follow |
|---|---|---|---|
| 01. | Electric Producing Company | Cooler summer means lesser electricity consumption means lesser profit | Temperature |
| 02. | Amusement Park | Visitors reduced due to rainfall | Rainfall |
| 03. | Woolen Garment Manufacture | Warmer winter leading to poor sale | Temperature |
| 04. | Wind Power Structure | Reduced power generation due to wind speed | Wind speed |

## Type of Weather Derivation

A call contract involves two parties, a buyer and a seller. The party agrees on a contract period and a weather index (W) that serves as a basis for the contract. W is the total precipitation during the contract, Stock (S) is the threshold temperature which is negotiated between the buyer and the seller. This seller sells the product at a premium to the buyer.

At the end of the contract, if K is a factor (tick) that determines the amount of payment per unit of weather index, the seller will pay P to the buyer or the derivative.

P = K (W-S)

In a put, the seller pays the buyer if W < S.

The payment is equal to

P = K (S-W)

### Under Linear Payment

Pput = Kmax (S-W, 0)

Psell = Kmax (W-S, 0)

### Under Binary Payment (fixed)

Pput = Po if S – W > 0 = 0, if S – W < 0

Psell = Po if W – S > 0 = 0 if W – S < 0

$$*HDD = \sum_{i=1}^{N} \max(O, 65^\circ F - T)$$

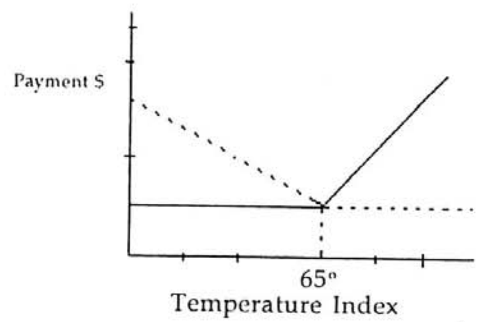
$$*CDD = \sum_{i=1}^{N} \max(O, Ti - 65^\circ F)$$

N = Number of days are the contract period.

T i = Average of the observation daily max and min temperature on $i^{th}$ day.[1]

This can be depicted in the figure.

Figure 1: Weather Index at 65° F cut off




### Calculation of HDD and CDD for a Period of and Days

WBAN calculation of HDD (Base temperature = 65° F )

| Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total HDD |
|---|---|---|---|---|---|---|---|---|
| Aug- daily temperature | 50 | 48 | 55 | 67 | 61 | 51 | 49 | |
| HDD | 15 | 17 | 10 | 0 | 4 | 14 | 16 | 76 |

WBAN calculation of CDD (Base temperature = 65° F)

| Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | TotalCDD |
|---|---|---|---|---|---|---|---|---|
| Average temperature | 76 | 66 | 64 | 60 | 68 | 70 | 74 | |
| CDD max (0, daily average temperature base temp. | 11 | 1 | 0 | 0 | 3 | 5 | 9 | 29 |

WABN derivative a parameter geographic location where temperature is observed.

*Source:* Weather Derivative: Instruments and Pricing Issue *by Mark Garman, Cales Blaneo and Rabut Erickson – March 2000 (c) Financial Engineering Associates*

• HDD is Heat Degree Days and CDD is Cold Degree Days which are calculated from selected cities in USA when 65° F is taken as a base temperature. Cities include Atlanta, Chicago, New York and Philadelphia in the US.

## Pricing Model

Most of the pricing models available in weather derivative are actually temperature-dependent and hence expressed in terms of HDD and CDD.

The computation of price for weather derivative requires time data of weather with continuous references. Such data helps in arriving at expected future value of cold/warm temperature based on predicted low-regional weather condition.

In predicting weather forecasting, meteorological data to price a weather derivative, the traders use the concept of 'look-back period'. The look-back period of time is used to estimate average temperature and volatilities. To build a program forecast, weather data for a period of 10-20 years in required. As a consequence, the industry is still in a nascent stage and acceptable pricing models are yet to be developed.

### The Failure of Black-Scholes Model in Pricing Weather Derivatives

Black-Scholes model is based on a tradable/priced underlying asset which has a proxy. In the case of weather derivative, this is the greatest problem, since weather conditions have neither price nor proxy and are erratic.

Another key point in the Black-Scholes formula is that we assume we are operating in a risk-free world and that inventories are therefore, happy earning the risk-free rate of return.

Besides, weather does not move in the same way an asset moves i.e., 'random walk'. In principle, say temperature can be 0° F to an infinite heat level, but tend to remain in a narrow band because of mean-reverting tendency.

## Some Methods of Pricing Product in Weather Derivative

### Burer Analysis

Burer analysis is essentially an insurance technique when industry prices a product which it has not primarily sold or where there is no data available for comparable product. Therefore, it is based on a pre-emptive question as to how much could the insurance company pay out if it would have sold a similar product in the last 50 years.

The process is divided into several steps. Initially, the historical data is collected and normalized. Then, the data is converted into degree—day (CDD & HDD) after which the portion paid at every year is followed. From this is obtained an average for the entire sample period. Then the figure is taken and discounted back to the settlement date. To this figure must be added a risk premium, which represents the margin for the insurance firm. However, it remains as a rough guide to pricing.

Mahal (2000) in a paper used two periods to show the shortcomings of the model. He used an Atlanta-based energy producer which noted high correlation between HDD index and demand for energy consumptions. The producer decides to hedge against the weather since it was cooler than it had been for the first quarter of the year 2000. The producer here can buy a call option with an excessive price of 1384.8 ( using a two-year average) for the index. The seller after a three-month call option with the payoff being $10,000 per index point with a maximum of $4.5 mn. Mahal calculated payoff at the option as $1,757,143 (using 21 yrs of data )after averages and discounting using months US money market rate, it stood at $1,728,123, (excludes writer margin).

Though expensive, it produces a hedge against a sudden increase in demand due to cold weather.

However, with a data of 10 years the discounted average would have only been $720,894. This brings us to second question such as, whether in determining pay-offs, should present value of today be taken or not. And whether the data period used reflects the current trends or not?

### Temperature-based Models

The temperature band models are used to use weather directly. In the first instance, data (CDD & HDD) is checked for any problem of inconsistency.

Then a statistical mode of the weather is created. A Monte Carlo simulation could be used to determine multiple weather patterns. For each weather pattern, a payoff would be determined. The average for all the payoff would be calculated. This would be discounted back to the settlement date.

Nelken (2000)[1] used a single Gaussian model which decides the following process:

dr[2] =a (b – r)dt[3] + Sdz

where,

r = risk neutral process,

a = speed of mean reversion,

b = mean interest rate (temperature),

S = the volatility and

Sdz = Weiner process (Normally distributed Stochastic term)

Mean reverting is a process whereby the increase in the parameter leads to slowdown of vector of another process; for example, very high interest rates tend to slowdown the economic process.

Weather can be said to be mean reverting as it is highly unlikely to deviate significantly from historical pattern.

The model above helps in reverting temperature to a mean value (depending on the time of the year) to forecast the temperature.

One good thing about this model is that it allows for negative interest rates. The weather can also become negative when temperature falls below zero.

The model is similar to an interest rate model, there are certain preferred factor that need to be considered:

- As the season changes so does the day mean temperature; therefore, the parameter 'b' in the formula needs to be adjusted. Nelken suggested changing b to b (i) which represents the mean for day number i.
- The validity of the weather is obviously affected by the season.
- The mean reversion rate 'a' is also affected by the season.
- Therefore, all the above parameters need to be changed to mean for day number i.

1 Nelken: Weather derivaties Pricing and Hedging, Super Computers Consultants Inc.
2 dr is the instances change in r.
3 dt is the infinite similarly small unit of time.

- The natural drift in the weather must be recognized.
- It is essential to calibrate the process to get the best match to the historical data.
- A Monte Carlo process will generate weather sequence and each sequence generates a payment for the option.
- The average of payments is discounted at a risk-free rate to give a fair value. Here, however, unlike Burer analysis, no risk premium is added.

## Equilibrium Valuation

Cao & Wei J[4] (2000) have looked at using an equilibrium valuation model for pricing a weather derivative.

Their research is significant for two reasons:

- It is a very lengthy and thorough work.
- They have worked at length with Chicago Mercantile Exchange (CME) and have published extensively about it.

Their paper looked at the following aspects:

- Preparing a general equilibrium model and specialize it to temperature derivative (Based on CDD & HDD).
- To determine a relation model for the dynamics of the daily average temperature.
- To find out whether the market price of risk associated with temperature significantly affects the valuation of temperature derivative.
- To develop a framework on the accumulation of HDD & CDD.

They initially established the set-up of the economic context, when there is a single investor with life time horizon and trading as a single risk stock (viewed as market portfolio). The investor invests in an investment (say bond) which has infinite number of contingent claims of any time. The agent's consumption is financed by a trading strategy. The investor's problem is to choose an optimum trading strategy.

They started with the Standard Euler equation:

$$X_t = ET\left(\sum_{\pi=1+1}^{\alpha} \frac{VL(Ct,\pi)}{Vc(Ct,t)} D_t\right) \text{.............................. (i)}$$

where, the price of any security is the sum of expect dividend discounted at the stockastic marginal rate of substitution. In equilibrium both financial markets and goods market clear so that aggregate consumption equals the dividend from the risky stock. Therefore, the price of a contingent claim with payoff 'qt' at a future time 'T', denoted by C, ( Ct , t) is:

$$C_t(t,T) = \frac{1}{V_c(\delta t, t)} E_t(V_c(\delta,T)_q)_t \text{........................ (ii)}$$

In particular at time 't' the equilibrium price of a risk-less bond paying one unit of consumption goods at T and O at all other times is:

[4] Cao & Wei J - Equilibrium Valuation of Weather Derivatives

$$B(t,T)=\frac{1}{U_c(\delta t,t)}E_t(U_c\delta_T.T),V_t E(O,T)\ ............(iii)$$

Contingent claim band upon the weather may be valued via (ii) ones the investors prefer, the dividends process and weather variable are identified. Cao & Wei J then used five cities to look at the dynamics and behavior of temperature.

Upon examination of the behavior it was found that there exists a correlation of above 0.84 among the temperatures of five cities, where the highest correlation was 0.98. It was also observed that three cities had large standard deviation indicating large temperature swings. The standard deviation of the monthly CDD for the two southern cities was higher while the reverse was true for HDD. Another point which was observed was that the daily temperatures had strong auto-correlation.

Cao & Wei identified some factors needed to be presented while modeling the daily temperature:

- Must capture seasonal pattern.
- Variation in the daily temperature must be around some rounded average.
- Must allow forecast to play a role in projecting temperature path.
- Incorporating an auto-regressive property in temperature change (a warmer day is likely to be followed by warm day and vice versa).
- The variation of temperature must be bigger in twist and swindle in summer.
- A projection for the future temperature should not be outside the normal range of the temperature for each projected point in time.
- Model must reflect the global warming trend.

It may be natural that all the above points need not necessarily be depending on the place under consideration.

Cao & Wei considered a mean diffusion but decided against this because it does not incorporate auto correlation in temperature movements. Instead, they resorted to a discrete auto-regressing model. They decided to (detrend) and demean the daily temperature as:

Uyr, t = Yyr, t - Yyr, t

yr = 1, 2, ......, 20.

t = 1, 2,..............365.

While the temperature is now detrended and demeaned it is wrong as the realized temperature may be above its historical daily average. It is possible however, to use it as a starting and make some specific adjustments so that the anchor points are in the middle of the varieties band.

The simple fourth step that Cao & Wei proposed is given below:

- For each month of the year calculate the average of the daily average temperature (there will be 12 for each year).
- Calculate the realized average temperature of each month.
- Find the difference between the actual monthly average in step (b) and the average from step (a).

- For each day of the month, adjust the historical average by the amount calculated in step ( c ). this temperature is reffered to as the adjusted temperature.

Cao & Wei assume the agent has constant relative risk aversion and that his/her utility is described by:

$$U(c,t) = E^{-\rho t} \frac{C_t^{\gamma+1}}{\gamma+1} \quad \text{..................(iv)}$$

Cao & Wei took a European option on a HDD ($T_1$, $T_2$) maturing at $T_2$ and an exercise price of X, C stands for call & P stands for put option. Using formula (2) and (4) we can obtain the following values for calls & puts:

$C_{HDD}$ (t, T, $T_2$,X ) = $e^{-p(T_2,t)} \delta_l^{-y} E_t$

where,

$\delta^{Y}{}_{T2}$ MAX(HDD($T_1$, $T_2$) − $X_2$))

$P_{HDD}$ ( t ,$T_1$ ,$T_2$ ,X ) = $e^{-p(T2,t)}$ $\delta_l^{-y}$ $E_t$

where ($\delta_l^{y}$ max ( X- HDD($T_1$,$T_2$) − X,0)

Options for CDD are similarly expressed.

$C_{CDD}$ (t, $T_1$, $T_2$ ,X ) = $e^{-p(T2-t)}$ $\delta_{l-y} E_t$

where,

($\delta^{y}{}_{T2}$ Max(CDD($T_1$, $T_2$) - X , 0))

$P_{CDD}$(t, $T_1$ ,$T_2$ X ) = $e^{-p(T2-t)}$ $\delta_t^{-y}E$

where,

($\delta^{4}{}_{T2}$ Max (X − HDD($T_1$,$T_2$) −X,0).

## Weather Derivative and Implication for Power Market

### Case I: Natural Gas Local Distribution Company (LDC) in North East of the US.

An interesting usage example is the case of natural gas LDC (LDC) in the North East which wishes to hedge against lower than expected revenues. This LDC sells natural gas to end-users of all the market segments—residential, commercial, and industrial. Since the LDC sells at known rate to its customers, all the variability in revenue comes from changes in the volume of sales.

During winter, natural gas sale goes up due to the interior heating. More severe the winter, more is the need for natural gas. If, on the other hand, the winter is mild, customers do not need as much natural gas for heating and gas sales in that period are low. Thus, the LDC is highly dependent upon winter temperatures.

It was found that there is a striking linear relationship between sales volume and HDD. For each incremental degree day, the LDC's customer essentially uses a constant additional amount of gas. In this case, HDDs are a good surrogate index for volume of sales.

If the LDC wishes to hedge its revenues (in effect, hedging volumes) it could do so with the use of weather derivatives based on HDDs. The LDC could do a couple of things. First, it could hedge put options or it cum HDD put option or it cold sell a cum HDD swap. Table 2 and Table 3 below give a comparison of outcomes from both hedges under different weather scenarios. This analysis uses the following assumptions; a normal winter contains 3800 cum HDDs, the LDC's normal revenue is $100 mn and its change in revenue with respect to temperature is $80,000 per HDD.

Using the put option, the LDC is protected on the downside mild winters but keeps the upside in the event of cold winter. On the other hand, if the LDC sold the swap then, it would essentially flatten out its exposure irrespective of the weather outcome. In either case, the LDC has protected itself from lower revenue from a mild winter.

**Table 2: Hedge with a Cum HDD Put Options**

| Type of Winter | Actual Cum HDD | Index Strike | Put Payment($) | Under Hedged Revenue ($) | Hedged Revenue($) |
|---|---|---|---|---|---|
| Mixed | 3,600 | -200 | 16,000,000 | 84,000,000 | 100,000,000 |
| Normal | 3,800 | 0 | 0 | 100,00,000 | 100,000,000 |
| Severe | 4,000 | 200 | 0 | 116,000,000 | 116,000,000 |

*Source: weatherrisk.e.symposium.com*

**Table 3: Hedge with a Cum HDD Swap**

| Type of Winter | Actual Cum HDD | Index Strike | Put Payment($) | Under Hedged Revenue ($) | Hedged Revenue($) |
|---|---|---|---|---|---|
| Mixed | 3,600 | -200 | 16,000,000 | 84,000,000 | 100,000,000 |
| Normal | 3,800 | 0 | 0 | 100,00,000 | 100,000,000 |
| Severe | 4,000 | 200 | (-)16,000,000 | 116,000,000 | 100,000,000 |

*Source: weatherrisk.e.symposium.com*

## Case 2: Finance the Purchase of a Peaking Power Plant with Weather Contract

Since power prices in the US tagged $7,000 per MWh in the summer of 1998, energy companies have been aggressively pursuing the opportunity to build peaking power assets. A peaking power plant can be viewed as a physical call option on temperatures. As temperature increases, the demand for power rises eventually to a point where it is economically viable to turn on the peaking plant. Below some critical temperature, the peaking plant is never dispatched.

The combination of regulation, transmission constraint and inelastic demand has created a unique opportunity where a single peaking power plant can be operational for only one day a year and still be economically viable. Weather derivatives provide an innovative method to finance the purchase and operation of these heavily-sought facilities.

Power plants are capital-intensive assets. A significant outlay of cash is typically required. A power company could finance the purchase of such an asset by selling a maximum temperature call option structure, say at 100°F. A maximum temperature call is a digital option structured such that the seller pays $1 mn if and only if the maximum strike of 100°F is exceeded. Here, the owner uses the option premium collected up-front to help finance the purchase of the peaking asset. The weather contract is designed to pay out only when the asset itself is producing an extraordinary profit (for example, when power prices are likely to exceed $500 per MWH).

Alternatively, interest or operational cost can be hedged with a weather structure; for example, that a particular peaking asset is economically viable at temperature above 95°F. This put option has a digital feature that pays a fixed sum if the maximum temperature never exceeds the strike level. In this way, a power company can successfully hedge against the severe economic loss that would be incurred in the event that power prices are unlikely to spike (mild summer).

## Conclusion

This article looks into various aspects of weather derivative—its nature, pricing mechanism, etc.—and at the end substantiates it with some US-based case examples to support the usage of weather derivative. The article is a trial to bring in a general understanding about weather derivative as a concept, which has yet to spread its wings in India.

*Reference # 6M-2008-03-07-01*