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Climate Risk, Temperature Dynamics, and Insurance in South Africa

Contents:

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Introduction

According to the UN's environmental programme, greenhouse gas emissions since the year 2000 have, at least until a small reduction during the 2008-2009 crisis, gone beyond the worst-case scenario predictions of the Intergovernmental Panel on Climate Change (IPCC). Global warming causes increasing droughts in large parts of the world. At the same time, the strength of tropical cyclones, typhoons and storms is increasing, with cloudbursts and floods washing away the fertile surface layer in previously dried-out areas. The December 2009 Climate change summit in Copenhagen was thus organised with the aim to find solutions for reducing greenhouse gases, set up an emissions verification system, and reduce deforestation.

Foundation has been laid for a new financial industry with carbon traders, carbon exchanges and a trade with derivatives that is based on the assurance to be able to buy carbon emission rights according to a certain price in the future. Weather derivatives are a growing derivatives sector the world over. They began to develop in 1997, as a result of El Nino. This caused companies that had earnings tied to weather to realise the importance of hedging their seasonal weather. Weather derivatives are valuable tools for risk management. Their payoffs are contingent on weather indices based on climatic factors.

The majority of weather derivative deals are carried out in the US, but there is a growing market of participants and contract types all over the world. The growth within Europe is occurring mostly in France and the UK, with Scandinavia and Germany close behind. Other parts of the world which have experienced growth include Asia, which has experienced rapid growth. Instruments of weather derivatives include swaps, options, option collars with payoffs dependent on weather related variables like average temperature, heating and cooling degree days (HDD and CDD), humidity, maximum or minimum temperatures. It is interesting to note that 1/7th of the industrialised economy is weather sensitive. Temperature related contracts are more prevalent, accounting for at least 80% of transactions, trading on the Chicago Mercantile Exchange (CME) for major U.S cities. The focus of this article is on temperature derivatives.

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A measure of the volume of energy required for heating during the day is referred to as a HDD where as a day's CDD is a measure of the volume of energy required for cooling during the day. The contracts are on the cumulative HDD and CDD for a month observed at a weather station. They are settled in cash just after the end of the month once the HDD and CDD are known. The buyer of the derivative is compensated by the writer for an amount that offsets the real business losses from adverse weather. To illustrate, an amusement park owner would buy a CDD put that pays out if there is a string of unusually cold days. The value accumulated with the long put position will help offset the lost revenue from customers who have stayed away during the cool weather period. If, on the other hand, the intervening period was unusually hot so that the CDD index rises well above the strike level, then the put expires worthless. The amusement park owner will have likely met desired risk management goals because increased business revenue compensates for the price of this "insurance policy". Of importance is to point out that weather derivatives differ substantially from insurance in that insurance contracts require the filing of a claim and the proof of damages with moral hazard playing a significant role. Insurance is also generally intended to cover damages as a result of infrequent high-loss events rather than limited loss, high probability events such as adverse weather conditions.

The use of weather derivatives in other industries and countries has not been widespread. Few exposures in other sectors of the economy experience such simple measurement. In addition, alternative uses may involve challenges in terms of non standardized situations and risks, contingent on illiquid, non-financial assets. This illiquidity issue is unlikely to change, as weather is by its nature a location-specific, non-standardized commodity. Other reasons fuelling lack of use include: lack of liquidity for specialised weather derivative contract, uncertainties to the pricing of these securities, availability of useful historical data, definition of an appropriate variable that is the source of uncertainty and the mere fact that weather is a non-traded asset and lack of organised market for weather derivatives as is the case of RSA.

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Data

The data set comprises daily maximum and minimum temperature records in degrees Fahrenheit. The analysis is conducted on the time series of average daily temperatures computed as the arithmetic mean of the daily maximum and minimum values. Johannesburg, Cape Town, Durban, Bloemfontein were chosen because they are the four major cities of RSA and also because accurate temperature records of 50 years are available for these cities at comparable weather stations[1]. The construction of the temperature record for each city is now discussed in detail.

Cape Town: The temperature record contains 18341 observations starting on the 1/1/1960 and ending on 31/3/2010. The time series is constructed from data collected from two weather stations. For Johannesburg, the temperature record contains 18341 observations starting on the 1/1/1960 and ending on 31/3/2010. The time series is constructed from data collected from three weather stations.

Durban: The temperature record contains 18341 observations starting on the 1/1/1960 and ending on 31/3/2010. The time series is constructed from data collected from one weather station. For Bloemfontein, the temperature record contains 18341 observations starting on the 1/1/1960 and ending on 31/3/2010. The time series is constructed from data collected from two weather stations.

"For Johannesburg, the temperature record contains 18341 observations starting on the 1/1/1960 and ending on 31/3/2010."

Table 1: Summary Statistics

	BLOEM	CPT	DURB	JHB
Mean	60.72256	62.31211	69.60246	60.85293
Median	62.06000	62.15000	69.71000	62.15000
Maximum	86.81000	86.36000	86.81000	82.13000
Minimum	31.64000	32.00000	32.00000	30.92000
Std. Dev.	10.82908	7.150938	6.185510	7.855664
Skewness	-0.229119	0.075014	-0.059700	-0.438172
Kurtosis	1.979572	2.307180	2.259852	2.513880
Observations	18341	18341	18341	18341

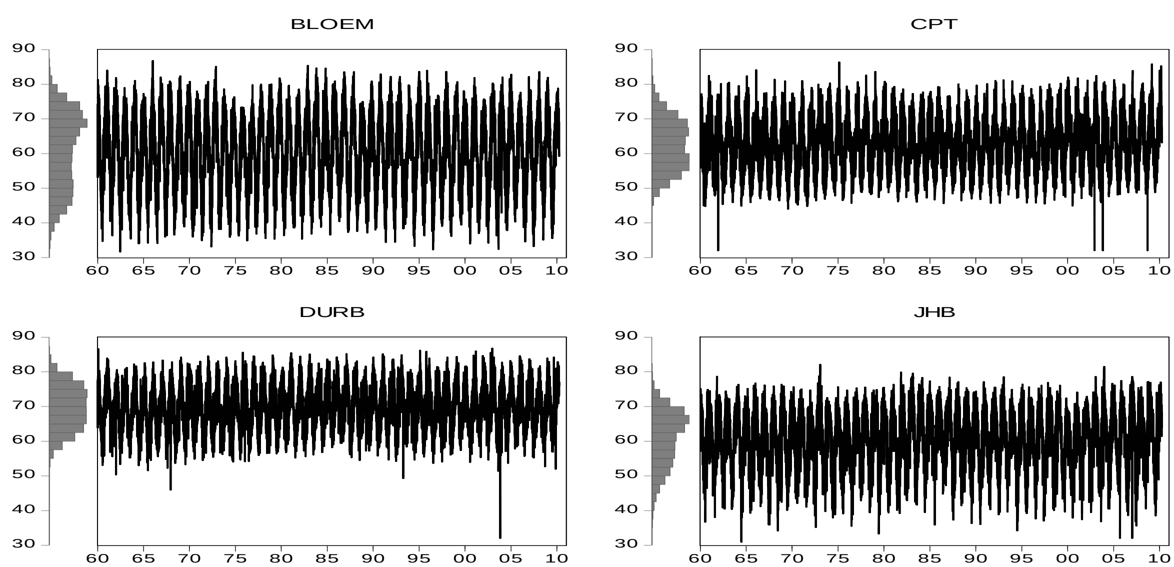
[1] All the data were supplied by the RSA Weather Services. For all the data sets, missing values were treated by averaging adjacent records. Following Campbell and Diebold (2004), all occurrences of the 29 February were removed.

From the table above, Durban is the hottest city on average and also records the lowest variability in average daily temperature. Bloemfontein has a relatively high variability in average daily temperature. There are differences in all the cities between the sample means of temperature for the individual sample as shown above. Literature abounds with various models for pricing weather derivatives. The results on the data behaviour suggested that a time trend will be an important component of a model of average daily temperatures for the four cities.

Skewness quantifies how symmetrical the distribution is. A distribution that is symmetrical has a skewness of 0. In the case of the results presented in the table above, the daily average temperature data area symmetrical since they are closer to zero. Kurtosis quantifies whether the shape of the data distribution matches the Gaussian distribution. A Gaussian distribution has a kurtosis of 0. A flatter distribution has a negative kurtosis, and a more peaked distribution has a positive kurtosis. For the four cities, the data have peaked distributions. This is confirmed by the diagram below.

The degree days used in weather derivatives are calculated as the difference in the daily average temperature from 65 degree Fahrenheit. A HDD is calculated by subtracting the daily average temperature from 65 degrees Fahrenheit. A CDD is calculated by subtracting 65 degrees from the daily average temperature. There cannot be both HDD and CDD within a single day, given that the daily average temperature can only be either above or below 65 degrees. If T is less than 65 degrees, HDD will accumulate where as if T is greater than 65, CDD will accumulate. In the southern (northern) hemisphere the HDD (CDD) season would be from May to September, while the CDD (HDD) season would be from November to March.

Figure 1: Average Daily Temperature 1960-2010



Statistical models for forecasting and pricing weather derivatives

A straightforward approach to evaluating the expected tick value of a temperature derivative contract is to model cumulative CDDs directly, on the assumption that there exist historic temperature records for longer horizon as cumulative degree days exhibit behaviour closest to normality. A simple quadratic trend model is proposed for cumulative CDDs as described by the general model below

$$C_t = \eta_0 + \eta_1 Trend_t + \eta_2 Trend^2{}_t + \in_t$$

Where $\in_t$ is now distributed, thus having the same probability distribution and mutually independent. Estimation for the parameters of this model for model yields:

The descriptive statistics for cumulative CDDs show that for Jhb and Durb, the distribution of cumulative CDDs are slightly skewed to the right as evidenced by the mean which are greater than the median. For Cpt and Bloem, they are slightly skewed to the left. Jhb records the least standard deviation. These features of the distributions are also apparent from the diagram of the cumulative CDD in the figure below. The CDDs appear as reasonable to favour historical records to price temperature-based derivatives. However, following conventional approach we can conclude that there is evidence that the cumulative CDDs are not identically distributed as marginal distributions mask the fact that CDDs are strongly correlated over time (Clements et al (2008). This confirms the unreliability of simple pricing based on historical records.

$$E(Ct)_{\text{Cape Town}} = \underset{(0.0954)}{6.25} - \underset{(0.0086)}{0.0022Trend} + \underset{(0.0002)}{0.0000Trend^2} + \underset{(0.1451)}{0.246e_t}$$

$$E(Ct)_{\text{Johannesburg}} = \underset{(0.1610)}{5.83} + \underset{(0.0146)}{0.0095Trend} - \underset{(0.0003)}{0.0001Trend^2} + \underset{(0.1422)}{0.2889e_t}$$

$$E(Ct)_{\text{Durban}} = \underset{(0.046)}{7.17} + \underset{(0.0042)}{0.014Trend} - \underset{(0.0000)}{0.0003Trend^2} \underset{(0.1570)}{-0.0585e_t}$$

$$E(Ct)_{\text{Bloemfontein}} = \underset{(0.1037)}{6.77} - \underset{(0.0094)}{0.0380Trend} + \underset{(0.0002)}{0.0008Trend^2} + \underset{(0.1375)}{0.5328e_t}$$

The figures in parenthesis are the standard errors. Durban and Bloemfontein have the trend and quadratic trend terms significant. Johannesburg has a trace of a trend and Cape Town has a trace for a quadratic term. The results are supported by the time series plots of cumulative CDD in figure 2 below.

Table 2: Summary Statistics CDD 1960-2010

	Cape Town	Johannesburg	Durban	Bloemfontein
mean	607.8	404.5	1479.6	693.1
median	610.4	398.6	1454.9	705.4
sdev	146.7	134	186.9	202.6
max	1229.9	717.8	2511	1138.4
min	325.1	94.2	1054.1	304.1

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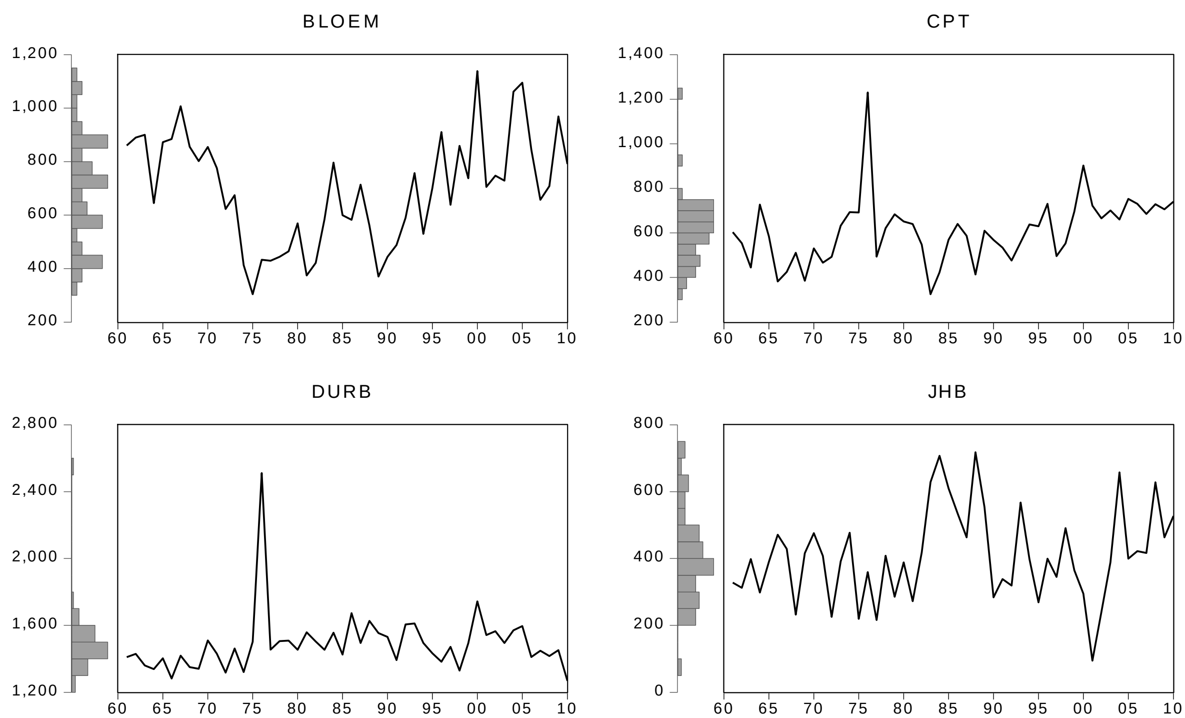
Simple pricing models can also be constructed using a probability distribution fitted to a historical data set of monthly CDDs or HDDs. Thereafter, the next step will be to integrate the product of the probability distribution with the payoff of the option. The expected payoff of a CDD option, or its theoretical value, is simply determined by:

$$(1) \quad M \int_{CDD=0}^{\infty} P(CDD)Q)CDD)dCDD$$

Figure 2: Cumulative CDD 1960-2010



Where P(CDD) is the probability distribution of CDDs, Q(CDD) is the payoff of the option in units of CDDs, M is the number of dollars specified in the contract per CDD, and d(CDD) is the differential. The expected value changes as a function of the strike, the probability distribution of CDDs, and the number of dollars per CDD. A simple, and quite often sufficient, formula for pricing individual options can been derived for the case of a Gaussian distribution of CDDs or HDDs. Assuming that one knows the mean (average) and standard deviation of CDDs or HDDs in a location, it is simple to approximate the price of an option. The algebraic expression relates the price of an option to three factors:

1. The standard deviation of the distribution;
2. The distance of the strike from the mean value;
3. The number of dollars per degree day specified in the contract.

If we define a normalized strike in terms of the number of standard deviations of the strike away from the mean value, the cost of the option is easily calculated from the relationship below

$$(1)\quad Y = -0.03X^3 + 0.22X^2 - 0.5X + 0.4$$

Where Y is the expected value of an option and X is the standard deviation of the strike price from the mean.

Option Value:

Cape Town = R R10 000* 0.27*147=R396 900

Johannesburg = R10 000 * 0.66* 134 = R884 4000

Durban = R10 000* 0.4* 187 = R748 000

Bloemfontein = R10 000* 0.33*203 =R669 900

The expected value does not include the "risk premium" that the writer of the option charges for carrying the risk. Nevertheless, this simple formulation provides a baseline from which to price an option. The largest challenge facing the options market participant is determining the mean and standard deviation to use as the model input.

Table 3: Estimate computation of Option Value using CDD

	Cape Town	Johannesburg	Durban	Bloemfontein
Mean	607	405	1480	693
Standard Deviation	147	134	187	203
Strike Value	800	600	1800	800
X axis	0.31	0.48	0.22	0.15
Y axis	0.27	0.66	0.40	0.33
Specification	R 10 000/Degree [1]Day	R10 000	R10 000	R 10 000/Degree Day

Conclusion

The article presented the role of weather derivatives as a tool for risk management. As an alternative class of financial instruments, weather derivatives go a long way in improving the risk-return trade-off in asset allocation decisions. Moreover, unlike insurance, the financial products based on weather allow companies either to be covered against climatic risks and also to make profit by speculation. A simple model can give a rough idea of what an option should cost. However, accurate models are needed in order for weather derivatives to be widely used as risk management tools. The fineness of such models would be reflected in the correct representation of the true value of the claim on a CDD index.

The challenge remains in that there is a considerable level of complexity to attain a correct model since amongst other factors; weather is a non traded asset. The general model which has gained favor with regards to accuracy is the Mean Reverting Brownian Motion (MRBM) process with first order autoregressive errors and a log normally distributed jump term. Other valuation approaches on weather derivatives in use include temperature stochastic models and the actuarial approach or "Burn Analysis" method. The use of the weather derivatives in RSA could constitute a good instrument to cover against weather risk.

[2] Assumption for demonstration purposes.