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Using Weather-Related Derivative Products for Tourism and Hospitality Businesses

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1. Introduction

Weather risk is a crucial element of overall risk management for a wide variety of businesses (Cao, Li & Wei, 2003) in energy, agriculture, food, tourism and hospitality sectors. Particularly, hospitality businesses such as hotels, restaurants and cafes are highly vulnerable when faced with unexpected weather conditions. For instance in a major metropolitan city like Istanbul, a five-degree-drop in temperature in summer, may cause many city-break tourists to stay indoors rather than to go out and spend their money in restaurants and cafes.

In fact, the global economy is exposed to significant amount of unmanaged weather risks and recent data show that the growth in this market will be substantial in the future. The Meteorological Office in the United Kingdom estimates that 70% of UK firms may be affected by the weather (Met Office, 2001). According to Weather Bill (2008), over 25% of the world economy is weather sensitive, with exposure approaching 50% in a number of countries. According to this study the world output could grow by as much as $ 258 billion per year if the 68 sampled countries actively hedged their weather risk, which is estimated to be about $ 5.8 trillion.

Although the growth of the weather derivatives market is largely attributable to the deregulation of the energy sector, other businesses such as supermarket chains, leisure, tourism and entertainment industries, agriculture and even consumers are the potential users of weather derivatives, to hedge against the vagaries of weather.

By its nature the weather is local and non- traded phenomenon and the market for weather derivatives may remain local and illiquid. The weather derivative products also provide a protection based on the measured values of the weather itself, not on monetary values. In other words, they cover volumetric risks which stem from the weather conditions. These conditions are related to variables including temperature, humidity, rainfall, snowfall, frost or wind, particularly in non-catastrophic nature. Weather derivatives are different from insurance products. While standard insurance instruments insure against high risk low probability events and they require the proof of loss together with the existence of insurable risk, weather derivatives allow payoffs which are free from these limitations and hence

allow a much greater flexibility both for the seller and the buyer. In addition to that, weather derivatives allow to hedge business risks relating to externalities e.g., good weather conditions somewhere else may influence the crop prices in some other places irrespective of the local weather conditions (Campbell & Diebold, 2005).

Weather derivatives instruments include swaps, futures and options which provide certain pay-offs to its users. This empirical study covers only options on weather temperatures which are bought and sold OTC (Over the Counter) and also traded in organized exchanges.

2. Weather derivative instruments

The options and futures written on temperatures are primarily based on temperature indices like Heating Degree Days (HDD), Cooling Degree Days (CDD), Cumulative Average Temperature (CAT) and also some Asian indices based on averages, so called Pacific-Rim index.(See F. E. Benth & J.S.Benth 2007 for the details and definitions). In this chapter, HDD and CDD option pricing is particularly examined.

Let T_i be the average of daily minimum and maximum temperatures in degrees Celcius on a particular day at a specific location. Then, Cooling Degree Days, (CDD) is defined when the temperature is above some reference level (for example 18°C for many applications) as a number of the value of max(T_i – 18,0) and Heating Degree Days, (HDD) as a number of the value of max(18 - T_i,0) , when the temperature is below some reference level. Then, over a period say, one month or winter/summer season or for a period of 45 days etc., accumulated number of heating degree days and cooling degree days are defined as

$$X_T = \sum_{i=0}^{T} HDD_{T-i} \tag{1}$$

and/or

$$X_T = \sum_{i=0}^{T} CDD_{T-i} \tag{2}$$

where T_i is defined by

$$T_{i=} \frac{T_{max} + T_{min}}{2}$$

Assuming there is a predetermined number of days in terms of temperature, K , there might be derivative contracts on these accumulated numbers such as swaps, forwards and options with payoffs (Q)

$$Q(F) = \Theta(K - X_T) \tag{3}$$

or

$$Q(F) = \Theta(X_T - K) \tag{4}$$

for future and swap contracts and

$$Q(P) = \Theta_{max}(K - X_T, 0) \tag{5}$$

or
$$Q(C) = \Theta_{\max}(X_T - K, 0) \tag{6}$$

for put and call options where the Θ is the point value of the payoff and K is the predetermined price or strike price of the contract. P and C denote put and call options respectively. The value of a degree day index, Θ, i.e. tick size, is accepted to be $ 20 in the CME (Chicago Mercantile Exchange).

There are also contracts written on Cumulative Average Temperatures (CAT) over a predetermined period. This can be shown with the following payoff functions where

$$X_N = \sum_{i=1}^{N} T_i \tag{7}$$

$$Q(F) = \Theta(K - X_N) \tag{8}$$

or
$$Q(F) = \Theta(X_N - K) \tag{9}$$

for swaps and futures and

$$Q(P) = \Theta_{\max}(K - X_N, 0) \tag{10}$$

or
$$Q(C) = \Theta_{\max}(X_N - K, 0) \tag{11}$$

for put and call options respectively.

For instance assume that the level of temperature is over the seasonal average in a particular winter season in a particular location. This means that the HDD is lower than the average. In this case, most probably, gas or energy companies will fail to sell enough energy products and hence will not be able to make adequate profits in that season. Then, it may be a better policy to sell HDD put at strike levels equal to average or slightly above average level of seasonal temperature levels. At the very extreme case individual consumers may buy calls on HDD to protect themselves against inflated gas bills due to the harsh winter conditions causing high HDD. Then, consumers may require calls on HDD at a strike level which is equal to average or slightly below average. In the section 5 an example of HDD option is presented for a restaurant –cafe chain.

For the summer season the paradigm changes. When the temperature degree is close to 18 °C centigrade this will cause a lower CDD and the summer business requiring warmer days will face a decline. This may mean that hospitality businesses such as hotels and restaurants, and energy suppliers, etc. may demand puts on CDD at a strike level equal to average CDD or at a level slightly above average. Similarly, in an extreme case the individuals and energy consumers who are uncomfortable because of the hot weather may demand call on CDD at a strike level equal to average CDD or slightly below the average. In this case they may be in a position to pay higher energy bills due to warm weather, but having to compensate from CDD contract.

Then, the pricing relationship can be written as the present value of an expected value of the specific payoff, plus a risk premium, i.e.:

$$S = e^{-rt} \left[E\big(Q(.)\big) + \lambda \right] {}^{1} \tag{12}$$

where S, $Q(.)$, λ denotes to price of the option , put or call function and the risk premium, respectively. Starting from the "0" lower bound for the integral a general formula can be stated as

$$S = e^{-rt} \left[\int_0^\infty Q(x)p(x)dx + \lambda \right] \tag{13}$$

where $p(x)$is the density of the probability distribution function. The derivative security payoffs are presented in continuous setting in Benth and Benth (2007), and J.London(2007).

A standard weather option can be formulated by specifying the following parameters;

a. An official weather station from which the temperature data are obtained
b. The contract type (e.g., future, swap, call, put)
c. The underlying index (e.g., HDD, CDD, CAT)
d. The contract period
e. The tick size, θ
f. The strike level, K
g. The maximum payoff (if any)

In general, conditions (b) and (c) are determined together according to a risk position of which a business firm is exposed to. The condition (g) means that whether the payoff of the option is limited or capped by a certain amount. These types of contracts are called capped options. The type of weather derivative securities is not limited to the ones mentioned in (b). In addition to these, collars, option combinations like straddles and strangles and some binary options are also traded in the market. The detailed closed-form pricing formulae can be found in Jewson (2003) for various distribution functions of contract payoffs.

The Weather Risk Management Association(WRMA) which represents the weather market reports that the total value of derivative contracts rose to as high as $ 45.4 billion in 2006, the year after Hurricane Katrina, and amounted $11.82 billion in 2010. The readers are recommended to refer to www.wrma.org to keep up with various changes taking place in the market, discussions and composition of players in the market.

3. Weather derivative modelling

There are basically three methods used to estimate the weather behaviour and the parameters of pricing model.

i. Actuarial Method
ii. Historical Burn Analysis
ii. Dynamic Models

There is also a deterministic method of forecasting weather which can be used to project weather changes up to 10 days in advance. This information can be used within the option or future period and there may be some possibilities to create arbitrage trading over some

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[1] Discount factor may only be used for the expectation term as another version of the formula.

intervals repeatedly, if /when the contract period is intentionally kept short. However, this line of reasoning is mostly out of scope for weather derivatives literature.

3.1 Actuarial method

Actually this methodology is used basically by insurance companies and the probabilistic assessment and statistical analysis is required for the events to be insured. Based on the statistical analysis on historical data a probability is assigned to the insured event, and the insurance premium is calculated accordingly. However, this method is less applicable for weather derivatives for the underlying variables such as temperature, rainfall, snowfall, wind etc. which tend to follow recurrent and predictable patterns (Cao, Li & Wei, 2003). Yet, there is still room for the use of the actuarial method. For instance in the case of weather derivatives, particularly for certain rare events the actuarial method could be used. In a situation where the contract is based on a rare case such as an extreme heat or chill, or snowfall, then the method may become applicable.

3.2 Historical burn analysis

The historical burn analysis method evaluates the contracts based on historical data and the average of realized payoffs in the past. The option premium can be calculated for any period / month / season as long as the one has the relevant data. The simple way of option premium is calculated by following the below sequential steps:

a. The period is selected
b. The historical data is gathered for the selected period
c. The index values (HDD or CDDs of the period) are calculated for the relevant period of each year
d. Considering the prescribed value of K , payoffs are calculated for each year, e.g., for 20 years, the values of HDD call option payoffs as $\max(HDD_i - K, 0)$ $i = 1, 2.....20$ are calculated
e. Then the HDD call option premium is simply computed as the average value of the payoffs calculated in (d)
f. In general, it might be thought that the more the data go back in the history i.e., the longer the time series used, the better and more reliable is the amount of the option premium. However, as the derivative security's payoff depends on the future behavior of the weather rather than the historical data, it may not be a good idea to use burn analysis in pricing of weather derivatives. Secondly, both methods do not take the risk element into account. The market price of risk associated with the temperature as an underlying variable can be incorporated in dynamic models with future prospects.

3.3 Dynamic models

As an underlying variable, temperature is forecast by deterministic and stochastic processes in dynamic models setting. Due to the mean reverting feature of weather temperatures, almost all models use Ornstein – Uchlenbeck (OU) process, in addition to stochastic Brownian (and fractional) motion.

The deterministic part of the model involves trend and seasonal terms and stochastic part involves stochastic term (Brownian motion) in most applications. The reason is that the

temperature shows strong seasonal characteristic and recurring patterns. In addition to the mean equation of the model many dynamic models contain the conditional variance term in order to take the changing volatility of temperature into account. These models are called GARCH type models.

Another feature of the weather is that the (average daily) temperature exhibits high autocorrelation i.e., short- term behaviour of the temperature will differ from the long- term behaviour.

Considering all these facts, the following mean and conditional variance equations (Campbell & Diebold, 2005) can be employed respectively;

$$T_t^m = c_0 + c_1 t + \sum_{p=1}^{P} \zeta_p \cos(2\pi p d(t)/365) + \sum_{p=1}^{P} \gamma_p \sin(2\pi p d(t)/365) + \sum_{i=1}^{L} \rho_{t-i} T_{t-i} + \sigma_t \varepsilon_t \quad (14)$$

$$\sigma_t^2 = d_0 + \sum_{q=1}^{Q} \delta_p \cos(2\pi q d(t)/365) + \sum_{q=1}^{Q} \lambda_q \sin(2\pi q d(t)/365) + \sum_{s=1}^{N} \beta_s \sigma_{t-s}^2 + \sum_{r=1}^{M} \alpha_r (\varepsilon_{t-r} \sigma_{t-r})^2 \ (15)$$

$T_t, t, d(t), p, q$ represent the daily average temperature, trend term (total number of observations) and number of days in a year (365, showing periodicity), number of lags for mean and variance equations respectively. The other coefficients are the parameters determined by the model including autocorrelation coefficients ρ_{t-i}.

The estimation process can be decomposed into its sub-components as follows;

Daily Average Temperature = Trend $(c_0 + c_1 t)$ + Seasonal $(\sum_{p=1}^{P} \zeta_p \cos(2\pi p d(t)/365) +$

$+\sum_{p=1}^{P} \gamma_p \sin(2\pi p d(t)/365))$ +Autocorrelation part $(\sum_{i=1}^{L} \rho_{t-i} T_{t-i})$ +Noise term $(\sigma_t \varepsilon_t)$

After having the estimates of mean temperature for each day in a year, OU mean reversion process can be established by the following stochastic equation;

$$dT_t = a(T_t^m - T_t)dt + \sigma_t dW_t \quad (16)$$

where, a is the speed of mean reversion and W_t is the Brownian motion. The solution of the equation is

$$T_t = (T_s - T_s^m)e^{-a(t-s)} + T_t^m + \int_s^t e^{-a(t-\tau)} \sigma_\tau dW_\tau \quad (17)$$

(See Alaton, Djehiche & Stillberger, 2002 for the details and parameter estimation)

Then the option payoff and the premium can be calculated by discounting the expected payoff of the option based on the underlying index (HDD, CDD, etc.) accordingly as

$$X = e^{-r(T-t)} E[g(T_t, T_{t+1} \ldots \ldots T_T)] \quad (18)$$

Another alternative is to use simpler autoregressive (AR) models (See Davis(2000) for the details). These models do not require a complicated variance process and they are faster compared with GARCH models. Campbell & Diebold (2005), and Benth & Benth (2007) apply GARCH method in their papers, Caballero, Jewson & Brix (2002) use Autoregressive Fractional Integrated Moving Average (ARFIMA), Zapranis & Alexandridis (2008) use neural networks and wavelets and Brody, Syroka & Zervos (2002) apply Fractional Brownian Motion (FBM) in estimation of weather temperature for derivatives pricing purpose. For the models based on AR and GARCH Monte- Carlo simulations are applied for pricing derivatives as a complementary tool.

However, Alaton, Djehiche & Stillberger (2002), Benth & Benth (2007), Jewson & Zervos (2003), and Jewson (2003) provide closed form solutions for the expectation in (18) with specific boundary conditions. Jewson (2004) uses kernel densities (normally distributed) as an alternative.

As an example, for calls and puts based on the specific underlying such as HDD or CDD, the formulae produced in Alaton, Djehiche & Stillberger (2002) are as follows respectively;

$$Q(C) = e^{-r(t_n - t)} \left((\mu_n - K)\Phi(-\alpha_n) + \frac{\sigma_n}{\sqrt{2\pi}} e^{-\frac{\alpha_n^2}{2}} \right) \tag{19}$$

$$Q(P) = e^{-r(t_n - t)} \left((K - \mu_n)(\Phi(\alpha_n) - \Phi(-\frac{\mu_n}{\sigma_n})) + \frac{\sigma_n}{\sqrt{2\pi}} (e^{-\frac{\alpha_n^2}{2}} - e^{-(\frac{\mu_n}{\sigma_n})^2}) \right) \tag{20}$$

where μ_n and σ_n represent the average and variance of the underlying index for the relevant period which is shown by n, α_n is the parameter of the standard normal distribution $\alpha_n = (K - \mu_n)/\sigma_n$ and Φ is the cumulative normal distribution. These formulae in (19) and (20) are primarily for contracts during winter months which typically represents the period November-March. If the mean temperatures are too close or higher than the reference level, i.e. 18°C, which might be the case for summer months, Monte-Carlo simulations are recommended to be used, rather than these above formulae.

4. Model, data and the research

This section presents an empirical work on CDD and HDD option pricing and aims to compute CDD and HDD prices in large metropolitan city, Istanbul. The data provided by the Turkish Meteorological Office for the periods of 1975 – 2006 covering 11680 (11680 for maximum and 11680 for minimum daily temperature degrees °C) observations over a thirty-two-year period have been used for analysis.

The particular reason for choosing Istanbul as the context of the study is due to its significance in terms of being the financial, cultural and tourism capital of Turkey. It is believed that tourism and hospitality establishments (hotels, restaurants, beaches, cafes, etc.) may significantly benefit from buying weather options for hedging themselves against the weather risk.

In this section, pricing issues are discussed, and various models are applied for computing CDD and HDD option prices. The section is divided into four sub sections. In the first sub section pricing is carried out through AR model accompanied by a simulation study, together with option pricing using ADS model as a benchmark.

Second sub-section uses time series for modeling the temperature with GARCH/ARCH features. In the last sub-section, considering the distributional nature of the temperature data, Edgeworth adjusted probability densities are used to compute the option prices.

4.1 AR model and simulation

Davis (2000) assumes lognormal distribution for accumulated HDDs, and values the payoff function under the physical (objective) probability measure and in an equilibrium setting with reference to Lucas (1978). In this case the prices are Black-Scholes prices with modified drift and yield parameters and with the absence of trading involving both the risk free asset and underlying asset (weather). Davis' (2000) model is based on the relationship between the gas prices and the temperature degrees for HDD modeling.

The drift parameter is retrieved from the model arbitrarily by using the mean of HDD and assuming the option is at the money (Davis, 2000). Alaton et.al (2002) find the option prices as expected values after having computed the first and second moments of the data by using Ornstein – Uhlenbeck process and standard normal density function. Similar to implied volatility measure, Alaton et al. (2002) compute the market risk premium by replacing the market prices with the model prices.

Let's define $D_i = T_i - \overline{T}_d$ as the difference between the daily average temperature and long term (32 years) daily average temperature for $i = 1,.......11680$ and $d = 1,....365$. When $i = kx365$, $k \in I$, or $k = 1,....32$, d returns to 1.

Then, an autoregressive model can be formed as follows;

$$D_i = \sum_{k=1}^{n} a_k D_{i-k} + b\varepsilon_i \tag{21}$$

	E1	E2	E3
a_1	0.794299	0.972473	0.986606
a_2		-0.224342	-0.285633
a_3			0.063032
b	1.839110	1.792365	1.788953
R-squared	0.630888	0.649464	0.650848
Akaike info criterion	4.056526	4.005120	4.001395
Schwarz criterion	4.057157	4.006382	4.003287
Durbin-Watson stat	1.643628	1.971726	1.999835

Table 1. A Summary of AR Model Equations for (14) with 1, 2, and 3 lags. All coefficients are meaningful at % 99 confidence level.

There is no material difference between the equations; however the last equation (third order) has lower standard error (1.789 vs. 1.7924 and 1.8391) and DW statistics (1.9998 vs. 1.9717 and 1.6436).

As for correlations, almost all the coefficients are in between $\pm 2\dfrac{1}{\sqrt{T}}$, (only 8.th order lag is greater than 0.019 which can be regarded as meaningless), so the residuals can be considered as *white noise*. However, E2 and E3 do not meet the positive variance limitations and for the sake of positive unconditional variance the first equation is adopted parsimoniously.

Then, assuming the distribution of the differences is normal with mean zero; unconditional standard deviation of the residuals is calculated as

$$\sigma = \frac{1.8391}{\sqrt{1-0.7943^2}} = 2.9299 .$$

Then, the temperature differences D_i can be simulated over a certain period by using the equation (14) and the unconditional standard deviation 2.93.

Instead of annual data, had the computations been based on monthly data and monthly equations, which are more realistic when particular periods are considered, a different set of equations would have been computed. Here are the examples for the months of January and July, which are believed to represent the relevant winter and summer periods.

	January	July
a_1	0.760904	0.757173
b	2.196550	1.365194
t-Statistic	36.88670	36.53150
R-squared	0.578836	0.574026
Akaike info criterion	4.412662	3.461479
Schwarz criterion	4.417605	3.466422
Durbin-Watson stat	1.627530	1.883939

Table 2. A Summary of Monthly First Order AR Equations for (14) - (All coefficients are meaningful at % 99 confidence level)

Adding the long term averages to the simulated values according to the following equation

$T_i = \overline{T}_i + D_i \quad i = 1,.....31$, mean $\displaystyle\sum_{i=1}^{31} T_i = 193.92$ and standard deviation, 69.9855 are computed by simulation for the month of January. The average which is very close to historical temperature degree justifies the simulation work.

Then, the mean HDD is $18n - \displaystyle\sum_{i=1}^{31} T_i = 364.0795$ and standard deviation is the same (assuming no daily value higher than 18 degrees).

Accordingly, the unconditional standard deviation of residuals have been found as 3.385, 2.09, and 2.93 for three different periods (January, July and overall) respectively.

As stated above, due to the trade-off between the parameters, fewer numbers of parameters in the equations are preferred. This helps to avoid the possibility of negative unconditional

variance. As it may be easily noticed, the standard deviation of residuals in January is almost 61% more than that of July. This may be interpreted as one of the evidences of global warming effect which may have occurred over the period of 32 years in Istanbul.

The normality tests prove that the distribution of residuals of annual data and January, though not normal, can be considered as close to normal as the tails have more density weights compared to normal distribution. This occurrence particularly applies to January and July residuals (See Figure 1a, 1b and 1c). Because of this a special care needs to be paid to pricing particularly when it is for a summer period.
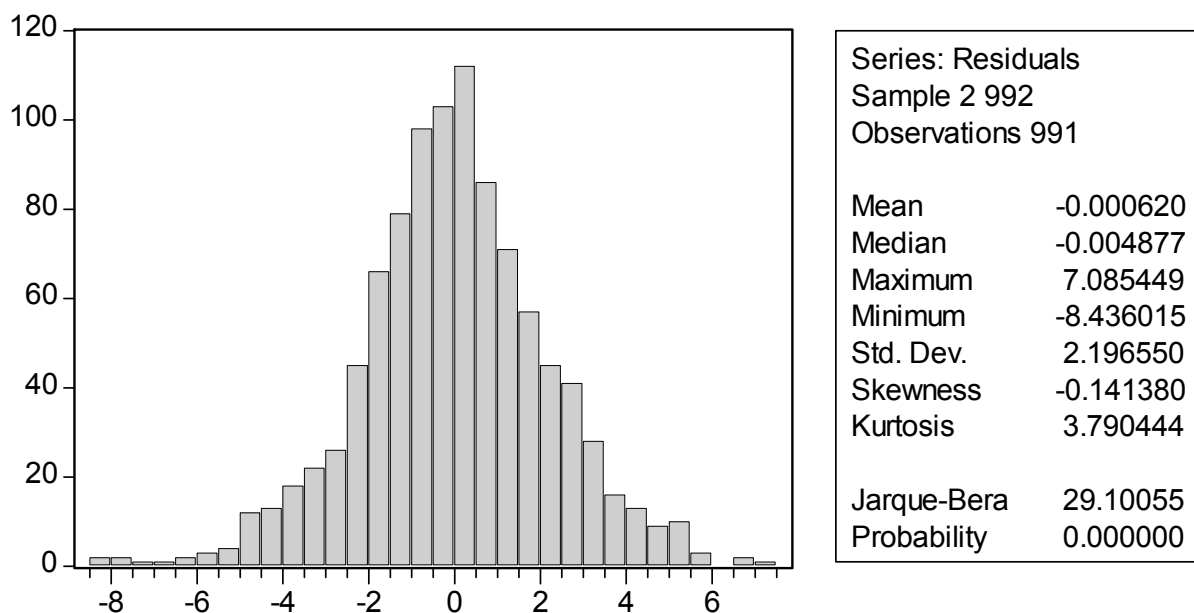

Series: Residuals	
Sample 2 992	
Observations 991	
Mean	-0.000620
Median	-0.004877
Maximum	7.085449
Minimum	-8.436015
Std. Dev.	2.196550
Skewness	-0.141380
Kurtosis	3.790444
Jarque-Bera	29.10055
Probability	0.000000

Fig. 1. (a) Histogram of residuals computed by using July data.

Series: Residuals	
Sample 2 992	
Observations 991	
Mean	0.005902
Median	0.128606
Maximum	4.752139
Minimum	-6.697494
Std. Dev.	1.365182
Skewness	-0.543268
Kurtosis	4.959596
Jarque-Bera	207.3079
Probability	0.000000
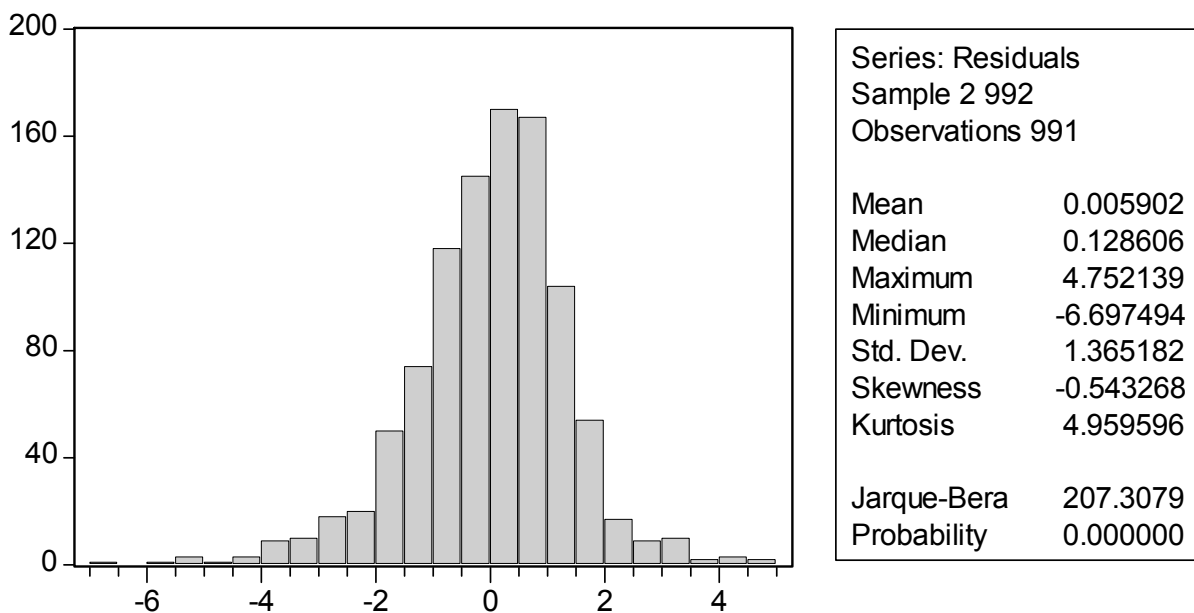
Fig. 1. (b) Histogram of residuals computed by using only January data.

Series: Residuals
Sample 2 11680
Observations 11679

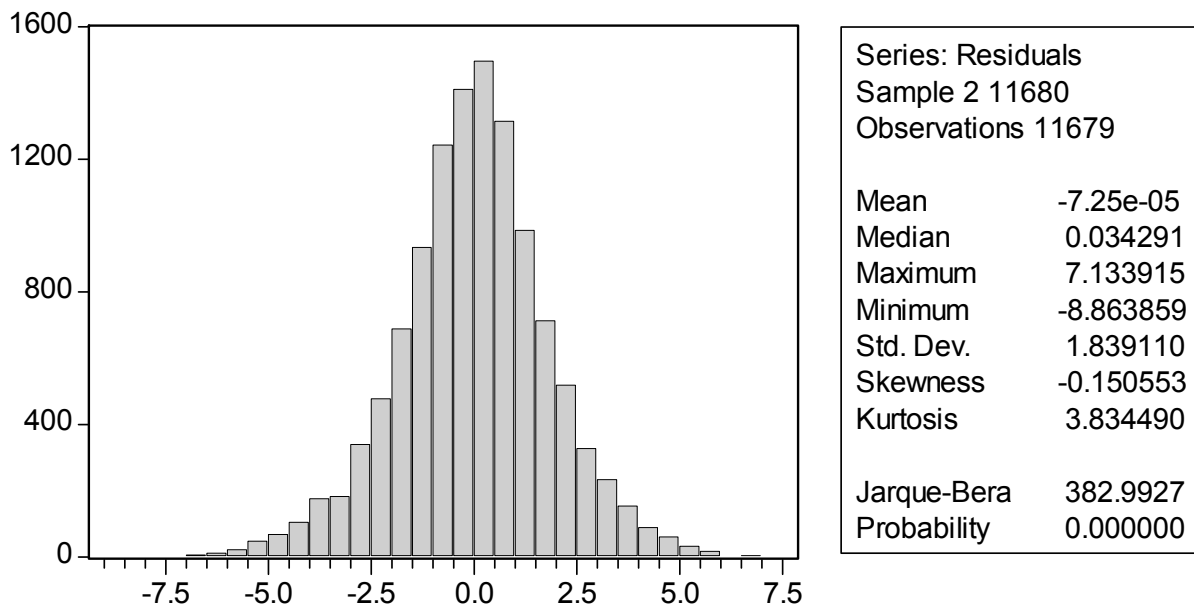|	
Mean	-7.25e-05
Median	0.034291
Maximum	7.133915
Minimum	-8.863859
Std. Dev.	1.839110
Skewness	-0.150553
Kurtosis	3.834490
Jarque-Bera	382.9927
Probability	0.000000

Fig. 1. (c) Histogram of residuals computed by using overall data.

The parameters used in simulation study are presented in Table 3 and Table 4 for two different periods.

Parameter	Number of Simulations: 20,000	Historical Long Term Average	Number of Simulations: 20,000	Historical Long Term Average
	unconditional SD of 2.93		unconditional SD of 3.3852	
Mean total degrees	193.92	193.53	194.02	193.53
SD of total degrees	69.99	40.37	80.44	40.37
HDD Mean	364.08	364.47	363.98	364.47
Log HDD Mean	5.88	5.89	5.87	5.89
SD of Log HDD	0.2023	0.11	0.2417	0.11

Table 3. Statistics of HDD for the Month of January by Using Unconditional SD of 2.93 and 3.385.

Parameter	No of Simulations: 20,000	Historical Long Term Average	No of Simulations: 20,000	Historical Long Term Average
	unconditional SD of 2.93		unconditional SD of 2.09	
Mean total degrees	742.35	742.84	742.55	742.84
SD of total degrees	69.88	36.90	49.60	36.90
CDD Mean	185.16	184.84	184.57	184.84
Log CDD Mean	5.1290	2.26	5.1797	2.26
SD of Log CDD	0.4903	0.086	0.3026	0.086

Table 4. Statistics of CDD for the Month of July by Using Unconditional SD of 2.93 and 2.09

As it is observed in the tables, the only distinguishing characteristic of the data is unconditional standard deviation incorporated into simulation work which is different from historical standard deviation. This figure *does* matter as well, between the summer and winter periods. The summer period shows less variability and has a lower volatility which may have implications for pricing. However, it is obvious that winter temperatures appear to be more volatile.

In conjunction with the above parameters, and considering the $\pm 1\sigma, 2\sigma$ of average CDD and HDD as strike prices, the call and put prices are computed in the following table according to the following expectations:

$$Put = \exp(-rT)E^P\left[\theta(K - X_T)\right]$$

$Call = \exp(-rT)E^P\left[\theta(X_T - K)\right]$, where X_T is CDD or HDD, $\theta = 1$ and with E^P as objective probability measure.

As the simulation work shows for CDD options, the higher the strike prices the higher is the difference between the call prices (maximum difference is at strike in the middle), computed by the two separate residual standard deviations, in terms of absolute and percentage terms(except the highest strike).The reverse is true for puts. For HDD options the higher the strike prices the lower is the difference between the put prices (maximum difference is at strike in the middle) computed by the two separate residual standard deviations and also the reverse is true for calls. The reason for this occurrence is that while the strike increases and puts come closer to deep in the money, the difference between the standard deviations have no significant effect on the prices. However, if puts are deep out of the money , the difference between the standard deviations are important and slight increase in volatility makes a susceptible increase in put prices. The same type of argument can be obviously made for calls.

Option	Strike Prices	Call Prices $\sigma = 2.93$	Call Prices $\sigma = 3.3852$	Put Prices $\sigma = 2.93$	Put Prices $\sigma = 3.3852$
HDD					
	224.1	139.64	141.34	0.57	1.26
	294.09	75.20	77.76	5.58	8.58
	364.08	28.19	31.28	27.48	32.08
	434.07	5.79	8.68	74.72	78.25
	504.06	0.66	1.27	139.66	140.10
		Call Prices $\sigma = 2.09$	Call Prices $\sigma = 2.93$	Put Prices $\sigma = 2.09$	Put Prices $\sigma = 2.93$
CDD	45.4	138.85	138.26	0.04	0.61
	115.28	70.99	75.41	1.82	5.81
	185.16	19.33	27.22	19.88	27.64
	255.04	1.74	5.56	71.64	76.15
	324.92	0.02	0.53	139.00	139.48

Table 5. CDD and HDD Call and Put Options computed by simulation, with residual standard deviations (σ) from the daily temperature model for the month of January (HDD) and July (CDD) using equation (14) . Interest rate is $r = 10\% p.a.$ (continuously compounded).

All these numbers are re-calculated by ADS formulae (ADS, 2002 p.15, equations 4.17 and 4.19) as presented in Table 6 below. Similarly, the difference is that the standard deviation and mean values of HDD and CDD are used in ADS formulae. The call and put prices of CDD and HDD options are almost the same with the ones computed in the simulation.

Option	Strike Prices	Call Prices $SD = 70$	Call Prices $SD = 80.44$	Put Prices $SD = 70$	Put Prices $SD = 80.44$
HDD					
	224.1	139.41	140.05	0.59	1.33
	294.09	75.19	77.79	5.78	8.48
	364.08	27.69	31.78	27.69	31.87
	434.07	5.78	8.44	75.20	77.95
	504.06	0.59	1.32	139.41	140.24
		Call Prices $SD = 49.60$	Call Prices $SD = 69.88$	Put Prices $SD = 69.88$	Put Prices $SD = 49.60$
CDD	45.4	138.06	139.19	0.32	0.03
	115.28	70.53	75.08	5.23	1.80
	185.16	19.33	27.65	26.82	19.90
	255.04	1.72	5.77	73.97	71.58
	324.92	0.03	0.59	137.81	139.19

Table 6. CDD and HDD Call and Put Options with Standard Deviations from the Daily Temperature Model and Historical Parameters for the Month of January (HDD) and July (CDD). Interest rate is $r = 10\% p.a.$ (continuously compounded).

The reason why two separate standard deviations have been used is due to the different residual unconditional variances (standard deviations), one being for the whole period, and the other one being for that particular month as referred in Table 4 and 5. The different residual unconditional variances used in the simulation produce obviously two different standard deviations for HDD and CDD.

4.2 GARCH modeling

When AR model with GARCH/ARCH feature is used, the following equations are used for computing the mean temperature and conditional variances.

The mean equation is

$$T_t^m = c_0 + c_1 t + \sum_{p=1}^{P} \zeta_p \cos(2\pi p d(t)/365) + \sum_{p=1}^{P} \gamma_p \sin(2\pi p d(t)/365) + \sum_{i=1}^{L} \rho_{t-i} T_{t-i} + \sigma_t \varepsilon_t$$

and the conditional variance equation is

$$\sigma_t^2 = d_0 + \sum_{q=1}^{Q} \delta_p \cos(2\pi q d(t)/365) + \sum_{q=1}^{Q} \lambda_q \sin(2\pi q d(t)/365) + \sum_{s=1}^{N} \beta_s \sigma_{t-s}^2 + \sum_{r=1}^{M} \alpha_r (\varepsilon_{t-r} \sigma_{t-r})^2$$

as mentioned in 3.3, as (14) and (15).

The parameters are presented in Table 7 below. The equations are then selected from a set of equations which provide minimum value of Akaike and Schwarz information criteria. Then these parameters are applied to simulation study to compute the option prices.

When the GARCH/ARCH modeling is employed to calculate the option prices, the critical point is that the pricing period on which the mean and conditional variance equations are applied is the same as the period these equations are obtained. In other words, the parameters of GARCH equations found using the whole number of observations causes the smoothing of the data for particular months and periods when they are used in the simulation application. Since the volatility structure is completely different for different months, overall GARCH equations may give biased results for particular periods.

	Whole period (E1)	July E(2)	January E(3)
c_0	3.028411	6.763988	1.781583
c_1	2.39E-05	0.000709	
ξ_1	-1.837887		0.301731
ξ_2	0.099831		
γ_1	-0.817157	-0.1633	
γ_2	0.066656		
ρ_{t-1}	0.961559	0.829327	0.921731
ρ_{t-2}	-0.251754	-0.126386	-0.200927
$\rho_{t-3}\ \rho_{t-1}$	0.047640		
ρ_{t-8}	0.025915		
σ_t	1.818203	1.3385	2.186813
d_0	1.586820	-1.448273	1.322562
δ_1	0.539787		
δ_2	-0.127277		
λ_1	0.485618		
λ_2	-0.101007		
β_1	0.411079		0.559813
α_1	0.111593	0.180305	0.171028
Adjusted R^2	0.94	0.61	0.60
Akaike	3.96	3.38	4.38
Schwarz	3.97	3.42	4.41
DW	1.96	2.02	1.96
F **Statistics (Prob)**	10801.33 (0.0000)	219.60 (0.0000)	244.55(0.0000)

Table 7. GARCH Equations for the average daily temperature of Istanbul using data of 32 years minimum and maximum daily temperatures. The total observation number is 11,680 for the whole period. The January and July periods have both observation numbers of 992.

Table 8 presents the prices of HDD and CDD call and put option prices computed by GARCH modeling of weather temperature for two different periods, namely, July and

January for 31 days, where 365 days is replaced by 31 days as shown in equations (14) and (15) above.

Option	Strike Prices	Call Prices for January Simulation number:20,000	Put Prices for January Simulation number :20,000
HDD	224.1	136.97 (143.39)	0.00(0.00)
	294.09	67.58 (73.78)	0.00 (0.00)
	364.08	4.31 (7.41)	6.16 (3.01)
	434.07	0.00 (0.00)	71.30 (65.06)
	504.06	0.00 (0.00)	140.89 (134.29)
		Call Prices for July Simulation number:20,000	**Put Prices for July Simulation number :20,000**
CDD	45.4	127.15 (134.85)	0.00 (0.00)
	115.28	57.88(65.22)	0.00 (0.00)
	185.16	0.23 (1.39)	11.55 (5.48)
	255.04	0.00 (0.00)	80.76 (73.36)
	324.92	0.00 (0.00)	149.98 (142.65)

Table 8. Simulation with GARCH. Simulation step 20,000, CPU time: 20 .56 seconds as average. The numbers in brackets are the computations made with the parameters covering whole year.

The call and put prices in Table 8 can be compared with i) the previous computations made in models 4.1 and, ii) the computations shown in the brackets, which have been obtained by using the parameters corresponding to the whole period. In this case when the GARCH/ARCH models are compared with the model in 4.1, it is seen that almost all strike levels of CDD and HDD have produced lower call prices compared to the other models. The situation is different for the put prices at some higher strike levels.

The reason for these biased results is that the equations for calculating January and July prices cannot produce the monthly average standard deviations of 3.38 and 2.10 °C - on a daily basis - for January and July respectively. In other words, simulated temperatures are quite close to averages. Then, since the calls get out of the money and puts get in the money as the strike level increases, an asymmetry, in favor of put prices, occurs.

On the other hand, as the comparison (ii), when the July and January prices are computed by the parameters belonging to the whole period, slightly higher call and slightly lower put prices are found.

To overcome this problem the parameters of January and July in Table 8 have been replaced by the parameters of the winter (November-March) and summer (May-September) periods in the simulation application. However, when this happens the situation gets worsened and the asymmetry between the call and put prices increases[2].

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[2] The results have not been presented here. They may be obtained from the authors.

4.3 Edgeworth density adjustment

The option prices for CDD and HDD have also been calculated using Edgeworth adjusted historical densities. There might be some situations requiring the changes in the prices due to the distributional characteristics of the data, particularly temperature data.

Due to non-normality the pricing needs to be modified by taking into consideration of moments of distribution higher than second order. This is the technique called "Generalized Edgeworth Series Expansion" and has been applied to option pricing by Rubinstein (1994 and 2000) Jarrow and Rudd (1982). In this chapter Rubinstein's (2000) approach has been adopted. In the model $a(x)$ is the density of normal distribution function which is extracted from historical distribution of temperature data by using first two moments. Then, by using skewness (ξ) and kurtosis (κ) measures of the historical data the densities can be modified and adjusted according to the following formula (Stuart & Ord, 1987):

$$f(x) = \Big[1 + (1/6)\xi(x^3 - 3x) + (1/24)(\kappa - 3)(x^4 - 6x^2 + 3) +$$

$$(1/72)\xi^2(x^6 - 15x^4 + 45x^2 - 15) \Big] a(x) \tag{22}$$

where x and $f(x)$ denote, standard normal variable and Edgeworth density of $a(x)$ respectively.

Accordingly, the adjusted (Edgeworth) densities can be calculated as weights of the put option payoffs during the selected period for the specific strike levels. The skewness and kurtosis adjusted call and put prices can be calculated according to the following formula:

$$C(E) = \exp(-r(t_n - t)) \frac{1}{\sum\limits_{j=1}^{N} f_j(x)} \sum_{j=1}^{N} f_j(x) \max(\sum_{i=1}^{D} X_i(t_n) - K, 0)_j \tag{23}$$

$$P(E) = \exp(-r(t_n - t)) \frac{1}{\sum\limits_{j=1}^{N} f_j(x)} \sum_{j=1}^{N} f_j(x) \max(K - \sum_{i=1}^{D} X_i(t_n), 0)_j \tag{24}$$

In the above formula K is the strike price, N is the number of observations (N=32 years), D is the number of days in a particular period which are January and July as example (D=31 days) and X_i is $\max(T_i - 18, 0)$ for CDD and $\max(18 - T_i, 0)$ for HDD.

As it is observed in Table 9 January/July data is left/right skewed as expected. Additionally, it is observed in Table 9 that CDD call and put prices computed by adjusted densities are lower than the prices computed by the equation (14). The reason for this difference is that, the weights or probabilities used in Edgeworth technique become lower at lower temperatures and higher at higher temperatures (strikes) due to its skew and kurtosis values. Since the calls get out of the money and puts get in the money as the temperature degree / strike level increases, this creates an asymmetry in favor of put prices and CDD put Edgeworth price is more than the others at the highest strike.

Option	Strike Prices	Call Prices (January) $SD = 40.38, \xi = -0.086$ $\kappa = -0.72$	Put Prices (January) $SD = 40.38, \xi = -0.086$ $\kappa = -0.72$
HDD	224.1	140.36	0.00
	294.09	71.04	0.09
	364.08	16.94	15.39
	434.07	0.13	67.99
	504.06	0.00	137.27
		Call Prices (July) $SD = 36.90, \xi = 0.452,$ $\kappa = 0.121$	Put Prices (July) $SD = 36.90, \xi = 0.452,$ $\kappa = 0.121$
CDD	45.4	132.74	0.00
	115.28	63.44	0.00
	185.16	9.58	15.44
	255.04	0.10	75.26
	324.92	0.00	144.46

Table 9. CDD and HDD call and put option prices by using Edgeworth adjusted densities for July and January.

As for HDD prices an opposite asymmetry is observed as expected. Only the deep in the money call has higher price than the prices computed by equation (14), and HDD put prices are lower at all strikes. The reason again stems from the fact that Edgeworth densities give more weighting to lower level of temperature degrees due to its skew. Since the low strikes are more in the money than the higher strikes, this causes an asymmetry in favor of calls.

Due to the continuous feature of the closed form formulae, the positive probabilities attributed to deep in the money and deep out of the money options there are positive prices whereas, in GARCH and Edgeworth density models there is no probability assigned to, for instance, strike levels 504.06 and 324.92 and no positive prices are available.

After having found the slightly different prices for different models and different standard deviations, there might be the question of *whether the computation of calls and puts should be seen as part of an ad hoc study*". This is partly true. It is highly recommended to estimate the unconditional standard deviations of residuals of temperature data and, in turn, estimate the standard deviation of CDD and HDD other than the historical ones at first. Then simulation with simple AR model and closed form formulas produce very close values for both contracts. On the other hand, sophisticated GARCH models may produce biased results and cause longer CPU times in simulations. The average CPU time is about 20 seconds per simulation for 20,000 steps. As pointed out by Jewson and Brix (2005) and Dorfleitner and Wimmer (2010) practitioners in general have a tendency to use index models not only because they require not so many parameters but also they are easy to understand and implement.

As a final check, the third and fourth moments of the data can be taken into account to fine-tune the option prices by transforming the historical probabilities through the Edgeworth expansion. This may not be so crucial in the context of temperature data, for the temperature data present strong seasonality and long term persistency which particularly may cause less weight in the tails. (Fat tails may be more common for some other weather variables such as rainfall and snowfall.) This is justified with moderate skew and kurtosis parameters as referred in Table 9. As a result of this, Edgeworth adjustments produce higher call prices compared to GARCH model but lower calls compared to AR and closed form formulas. As for puts, Edgeworth prices are always lower than the prices computed by all models except at the very high strikes for CDDs, e.g., 324.92 due to the unique characteristics of the data.

5. Example and the results

In this section, the financial implications of hedging is presented from the viewpoint of a restaurant-cafe chain purchasing a HDD January call option based on the temperature data of past 32 years.

It is assumed that restaurants or cafés in with a number of restaurants and cafés at various locations is exposed to weather risk and its outdoor business is rather susceptible to the changes in temperature degrees.

Another assumption is that a $1°C$ decrease in weather temperature in January may cause a proportionate decrease in the number of people demanding the services of this particular restaurant or café chain. It is also assumed that this decrease may, in turn, cause $750 decrease in net operating income based on the supposed value of θ. ($\theta = \$750$) Then to hedge against the changes in net operating income, the restaurant chain decides to buy a call option on HDD with a strike of 364.08 (historical average). The idea behind the call purchase is, if the winter gets colder than usually expected, i.e., HDD is above the strike, in spite of lost business due to the harsh winter conditions, the chain compensates the loss with the option payoff, which is the difference between the HDD at the maturity and the strike times $750 conditioned on the payoff being positive. In case the January HDD is just at the strike or below this level, restaurant chain loses the premium. In Table 10, it is assumed that the chain has bought a HDD January call with the strike of 364.08 during all these 32 years. The prices used in Table 10 are simulation prices (Table 5) and Edgeworth adjusted (Table 9) call prices. Accordingly, the restaurant or the café chain would make an overall loss with simulated (and with very close ADS prices as well) HDD call prices and make a very small profit with Edgeworth adjusted prices over the period. Assuming the risk hedgers are willing to make a loss to a certain extent, the example justifies the employment of such a hedging tool in order to smooth the possible fluctuations in net operating income. However the gap between the overall costs (-$266,453 and $3,547.5) points out two important facts. The first one is that there may be opportunities for the business to find better prices in the market. The firm may reduce the total cost by getting quotations between the "model prices" and "(Edgeworth) adjusted" prices depending on the value of θ [3]. Secondly, there have been years, providing the firm with significant amount of positive payoff from the HDD contract which would make the firm close the period with $ 3,547 profit from $266,453 loss once again subject to the value of θ.

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[3] Note that the value of $\theta = \$750$ is an assumed value.

Call Prices and θ	Annual Premium ($)	Number of years that the Firm makes profit	Net Hedging Gain/(Cost) for the Firm during 32 years ($)
$\theta = \$750$			
$HDDCall = \$28.19(Simulation)$	-21,142.5	10/32	-266,453
$HDDCall = \$16.94(Edgeworth)$	-12,705	11/32	3,547.5

Table 10. HDD example for a restaurant chain hedging against the weather risk in the month of January.

6. Discussion and vision for the industry

According to the World Tourism Organization (2009) Turkish tourism industry represents 2.5% of world tourism market, in terms of tourist arrivals and tourism revenues earned. As the second largest industry tourism plays a major role in the economy of Turkey. Between 1986 and 2006, tourism industry's contribution to the Turkish Gross Domestic Product (GDP) increased from 2.1% to 5.2% (TURSAB, 2008). Tourism also plays other significant roles in improving Turkey's other macroeconomic indicators. For instance, together with its direct and indirect contribution, tourism represents 17.9% of total employment in Turkey. Additionally, tourism revenues helps close the balance of trade deficit in Turkey, a country with one of the highest balance of trade deficits in the world. Turkey has the seventh largest balance of trade deficit in the world (World Bank, 2010), used to be the third in 1990s, and the contribution of tourism industry in Turkey towards closing balance of trade deficit ranged from 77% in 2001 to 56% in 2003. Moreover, Turkish tourism is important as it has the highest tourism multiplier value in the world (Fletcher, 1995). This means that any development in Turkish tourism may have significant implications for the whole economy.

However, alongside these above strengths Turkish tourism industry faces fundamental problems too, which may jeopardize its sustainable development. For instance, Turkish tourism is highly seasonal with about 70% of tourists visiting Turkey between April and September for sun and sea holidays (Koc & Altinay, 2007). On top of seasonality, which requires skills to manage both the peak season and off-season, weather risk creates additional burdens in terms of the sustainability of hospitality businesses such as hotels, restaurants, cafes, etc.

According to Culligan (1992) the tourist's increasing desire for more novel, adventurous, and 'authentic' forms of tourism experience is a function of the decline in utility associated with a decision to simply replicate previous experience. This implies a move away from General Interest Tourism (GIT) towards Special Interest Tourism (SIT) (Brotherton & Himmetoglu, 1997). Krippendorf (1987) argued that fundamental changes occurring in the tourism market in general are in line with the developments of new patterns of tourism consumption. He maintains that in the near future there will be a substantial decline in those tourists for whom hedonism is a dominant travel motive, e.g. as in the case of sun and sea holidays, and for whom tourism is seen purely as a mechanism for recovery [rest] and liberation [escape from the ordinary]. Instead, the travel market will place more emphasis on the environmental and social context in which tourism occurs, and the humanization

of travel activities (Krippendorf, 1987). In other words Krippendorf (1987) argues that there will be a move from GIT to SIT with decreasing utility in hedonistically motivated holidays. Zauhar's (1994) view also supports this trend pointed out by Krippendorf (1987). Zauhar (1994) claims that future projections, with reference to tourism trends, indicate a tendency pattern of breaking free time into a series of blocks, thereby permitting a variety of experiential stays within a single year (Zauhar, 1994). Therefore, based on the above explanations it may be suggested that there will be a decline in the numbers of organized mass tourists who visit Turkey primarily for sun and sea holidays. This means that the growth of Turkish tourism may not be sustainable unless corrective measures are taken both at macro level in terms of public policy and at micro level in terms of effective marketing and actvities financial management. From an effective marketing management diversification of tourism products can be suggested for sustainability in future. However, sustainability also requires financial robustness of tourism and hospitality businesses (Chang, 2009; Beyazit and Koc, 2010).

According to research carried by Haktanir and Harris (2005) there are six key themes in evaluating a hospitality establishment's performance. These are business dynamics, overall performance measures, employee performance measures, customer satisfaction measures, innovative activity measures and financial performance measures. In Turkey financial performance is especially an important issue, particularly due to strong seasonality and low profit margins. Especially coupled with the perishability nature of services (Zeithaml, Parasuraman, & Berry, 1985), tourism businesses usually find it difficult to sustain their existence, yet alone grow.

The particular reason for choosing Istanbul as the context of this study lies in its significance in terms of being the financial, cultural and tourism capital of Turkey. According to World Tourism Organization (2010) in terms of tourist arrivals Istanbul is among the top ten destinations in the world. It is believed that tourism and hospitality establishments (hotels, restaurants, beaches, cafes, etc.) may significantly benefit from buying weather options for hedging themselves against the weather risk.

This study has proposed a mechanism whereby hospitality establishments operating in Istanbul may reduce their vulnerability against the vagaries of weather. Especially, hospitality businesses such as restaurants, cafes and bars are extremely fragile not only due to high levels of seasonality and availability of rather low profit margins, but also due to the extensive adoption of all-inclusive pricing system by hotels and hotel chains.

The findings of the research may be used by hospitality businesses not only in Istanbul, Turkey, but also in other cities in the world as reference. Additionally, apart from tourism and hospitality establishments, many other businesses in various sectors, e.g. in energy, may benefit from the findings of this study.

In the pricing process of CDD and HDD options closed form formulae is recommended due to its simplicity and traceability. However, to be on the safe side AR models provide unconditional variances which may yield higher standard deviation parameters for CDD and HDD than the historical ones, which in turn produce better (higher) prices for the seller. The other model (GARCH) has not produced consistent prices for CDD and HDD options and hence is not recommended. The calculated prices have to be compared with the

(Edgeworth) adjusted prices to take into account the distributional characteristics of the HDD and CDD data.

The key point in pricing of weather derivatives is that the market is incomplete and it is impossible to buy or sell the underlying asset for hedging purposes. For that purpose sellers will try to charge maximum premium in their prices and quotations to avoid potential surprises regarding fluctuations in weather. In weather derivatives markets a ten to twenty percent addition can be made to the premium provided in (12) just like insurance premium mark-up, in the light of past experience gained over a period of time.

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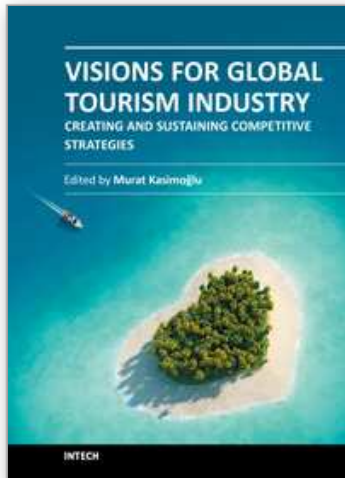
Visions for Global Tourism Industry - Creating and Sustaining Competitive Strategies

Edited by Dr. Murat Kasimoglu

We have been witnessing huge competition among the organisations in the business world. Companies, NGO's and governments are looking for innovative ways to compete in the global tourism market. In the classical literature of business the main purpose is to make a profit. However, if purpose only focus on the profit it will not to be easy for them to achieve. Nowadays, it is more important for organisations to discover how to create a strong strategy in order to be more competitive in the marketplace. Increasingly, organisations have been using innovative approaches to strengthen their position. Innovative working enables organisations to make their position much more competitive and being much more value-orientated in the global tourism industry. In this book, we are pleased to present many papers from all over the world that discuss the impact of tourism business strategies from innovative perspectives. This book also will help practitioners and academician to extend their vision in the light of scientific approaches.

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