CLIMATE VARIABLES AND WEATHER DERIVATIVES.
GAS DEMAND, TEMPERATURE AND THE COST OF WEATHER FOR A GAS SUPPLIER[Ψ]

Giampaolo Gabbi[#] - Giovanna Zanotti[*]

Abstract

The purpose of this study is to analyse the hedging capabilities of weather derivatives on the Italian energy sector. This is achieved through the investigation of the existence of a statistically significant relation between gas consumption and climate parameters. We investigate such a relation applying different models. The first is a simple regression where we estimate gas consumption, as the dependent variable, and temperature, rain, humidity and pressure as explicative variables. In the second model we introduce a derived temperature variable in order to better capture the non linearity behaviour of gas consumption. In the third model we implement lagged, other than present, weather variables. In the fourth we apply dummy variables to consider, daily, monthly and holiday patterns in gas consumption. In the fifth model, finally, we introduce an autoregressive structure in the error term. We then turn to estimate the cost of weather for a gas retailer operating in Milan and to design alternatives hedging strategies.

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[#] Professor of Banking, University of Siena, SDA Bocconi, Milan, Tel. +39-02 58366105. E-mail: gabbi@unisi.it

[*] Professor of Financial Markets and Institutions, Università Commerciale Luigi Bocconi, SDA Bocconi Viale Isonzo 25, 20135 Milano, Italy. Tel. +39-02-58365953. E-mail: giovanna.zanotti@uni-bocconi.it.

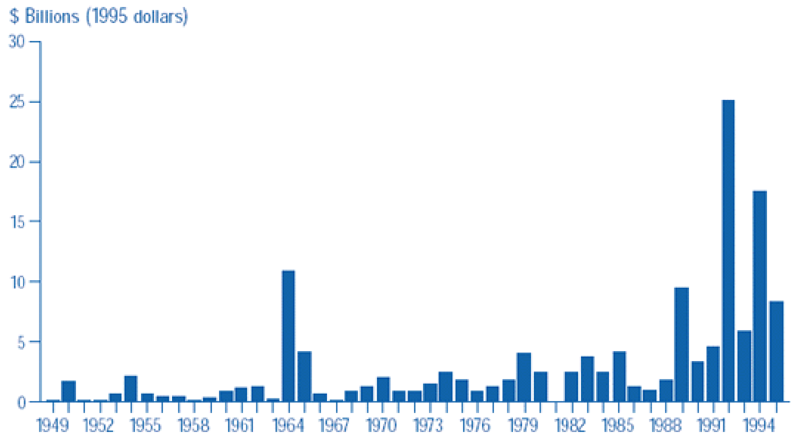
1. Introduction

Weather derivatives allow to hedge weather risk that is the financial gain or loss due to variability in climatic conditions. The market originated in 1998[2] when the US power community realised that the high volatility of revenues due to weather variability could be controlled and, since then, has grown rapidly both in terms of number of contracts concluded and notional value[3] and in terms of variety of industry applications. Economists believe that something like 70% of the economy is vulnerable to unpredictable weather patterns. Gas utility and gas distributor companies report severe drops in first quarter earnings when Winter months are milder than normal[4]. The quantity of energy required to heat or cool is strongly dependent on the weather: below normal temperatures in Winter create higher demand for heating; above normal temperatures in Summer create higher demand for energy to meet air conditioning needs. Energy companies are then strongly subject to weather variability. Agricultural companies may suffer serious loss due to below zero temperatures or other abnormal weather conditions. Ice cream and soft drinks sales revenues are seriously affected by cold or wet Summers. Extremely cold temperatures or lack of snow influences ski resorts. These are some of the many cases of companies whose performances are linked to climate. Weather derivatives can theoretically be designed for almost any weather variable (temperature, rain, snow, wind..) though most of the contracts have so far been constructed around temperature forecasts and temperature related underlying[5]. Weather derivatives contracts are in many aspects different from "standard" derivatives: the contract underlying (a weather variable) is not traded in a spot market, weather derivatives are useful to hedge volume risk, that is the changes in quantities supplied or demanded due to changes in climate, but not necessarily price risk[6]. Moreover, weather derivatives are very different from insurance contracts, since they do not require proof of damage and allow a bigger range of events to be hedged.

Weather derivatives can be assimilated to catastrophe hedging contracts. There are three basic approaches: Exchange Traded Derivatives (CBOT Cat Insurance Futures and Options and Bermuda Commodities Exchange Cat Options); Contingent Capital (Line of Credit; Contingent Surplus Notes; Catastrophe Equity Puts); Risk Capital (Catastrophe Bonds). They were firstly proposed by Goshay and Sandor in 1973
During last years, the volume of losses has increased (figure 1) but the opportunity to manage these kinds of risk with insurance contracts is usually evaluated in terms of moral hazard.

Figure 1 - Insurer Disaster Losses in USA (1949-1995)

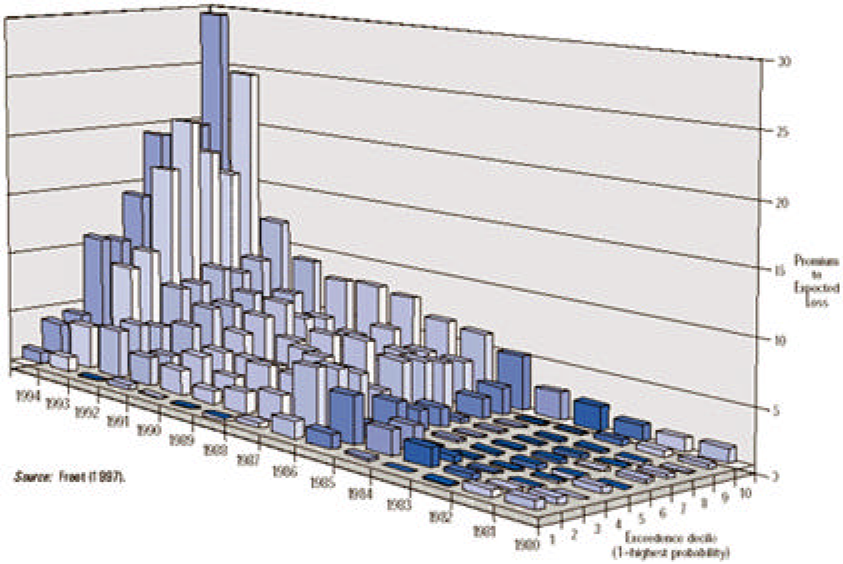
[2] The reason why the market originated in the power industry in 1998 is related to long term weather forecasts calling for warmer than normal weather and, as a consequence, for a remarkable reduction in electricity demand and in power industry revenues.
[3] According to the 2003 Price Waterhouse e Coopers survey the total notional value of weather contracts concluded in 2002-2003 was equal to 4,188 millions of dollars. The weather risk management association estimates a weather industry future growth up to 10 billion dollars.
[4] See the official site of weather risk management association www.wrma.org
[5] Price Waterhouse survey estimates that 90% of the total number of contracts concluded in 2002-2003 were temperature related ones.
[6] "Usual" financial derivatives hedge against price risk but not against volume risk although the two risks are obviously related. In this regard weather derivatives are complementary to traditional commodity and financial derivatives.



Moral hazard arises whenever an economic actor, by virtue of being insured, fails to take precautions to prevent the event being insured against. Reinsurance protection can relax the normal incentives for the primary insurer to underwrite carefully and settle claims efficiently.
The primary may become lax in its underwriting procedures, pay inadequate attention to its own spread of risk, and fail to provide adequate risk audits for potential new policies.
Moreover the primary may be able to avoid the abnormal transaction costs of settling claims, and even buy some goodwill with its policyholders by making generous settlements with policyholders and passing on the costs of excess settlements to its re-insurer.

These considerations explain why the insurance premium has deeply increased during the last decades (figure 2)

Figure 2 : Premium to Expected Loss, by Exceedence and Year (1980-1995)



Catastrophe options seek to control this moral hazard by using industry (or sub-industry) indices. The basic idea is to define the contract payoff in relation to some variable that is correlated with insurer losses but over which the insurer has little or no control.
Then when using catastrophe options, a primary insurer that is able to practice cost mitigation will receive much of the benefit of that activity in the form of reduced claims.

- Advantages
    - Low transaction costs
    - Reduction of adverse selection and moral hazard
    - Low default risk
    - Privacy
    - Flexibility
    - Standard contracts
    - No delay in payments
- Disadvantages
    - Market liquidity
    - Hedging imperfection

The same pros and cons can be considered for weather derivatives. In particular, the hedging imperfection is usually at the basis of market width.

The purpose of this study is to analyse the real hedging capabilities of weather derivatives on the Italian gas sector. This is achieved through the investigation of the existence of a robust statistically significant relation between energy, more specifically, gas consumption, and climate parameters. The proof that such a relation exists is, in fact, the first step of a valuable hedging strategy. There are several reasons why we choose to concentrate our attention on the energy sector. Among the different sectors affected by weather risk, the gas sector is one of the most sensitive. This is due to two factors: price and volume. Gas supply costs usually increase with cold weather and decrease with warm weather (price factor). Furthermore, the gas usage typically varies with changes in heating season weather. The gas producer or distributor profits strongly depend on volumes and the main driver of volume risk is weather. Most of the weather derivative contracts concluded up to now are related to the protection of utilities revenues against changes in temperature. In the United States the energy sector is the first for trading in weather derivatives. In order to access the possible development of such a market in Italy an analysis of the relationship between electricity consumption and weather variables must be undertaken. The second reason why we choose to concentrate our attention on the gas industry is that, although the impact of meteorological conditions on the energy and gas consumption has long been recognised, the sector deregulation process has given a growing importance to costs and revenues control. In fact, whereas in a regulated monopoly the rates, the customer base and the revenues are defined and controlled by the regulator, in a competitive market, rates and return are no longer set and certain but subject to competition. The high variability in the prediction of demand due to weather conditions could cause significant economic losses. Weather derivatives can compensate future possible losses and represent an instrument for ensuring revenues are attained even in a competitive and uncertain market. This topic is particularly important for Italy where the deregulation process is starting to be put in place. The third reason for focusing on the gas sector is connected to the relevant scientific interest in the relationship between gas and energy consumption and weather variables.

We investigate such a relation for the Italian Market, applying different models. The first is a simple regression where we estimate gas consumption, as the dependent variable, and temperature, rain, humidity and pressure as explicative variables. In the second model we introduce a derived temperature variable, the heating degree-day function, in order to better capture the non linearity behaviour of gas consumption. In the third model we implement lagged, other than present, weather variables. In the fourth model we apply dummy variables in order to consider, daily, monthly and holiday patterns in gas consumption. In the fifth model, finally, we introduce an autoregressive structure in the error term.

The paper is organised as follows. The next session will summarise methodology and results of previous studies on this topic. Session three will describe data. Session four will present methodology and results. Session five shows how weather derivatives can be used to hedge volume risk by a gas company. Session six concludes.

2. LITERATURE REVIEW

Bolzern, Fronza and Brusasca (1981) analyse the relationship between daily temperature and winter-daily electric load in Milan from Winter 1976 to Winter 1978. The study shows a significant relation between the two factors. The relation increases over time.
Al-Zayer e Al-Ibrahim (1995) estimate an econometric model to forecast electricity consumption in Eastern Province of Saudi Arabia. The results obtained using different econometric models show that temperature plays an important role in explaining the demand for electricity. They use either primitive variable (temperature) or derived variables (heating and cooling degree-days). The model with the derived degree day function shows a higher predictive power than the one with primitive, air temperature, variables.
Sailor and Munoz (1996) apply a methodology which involves the historical analysis of energy consumption (gas and electricity) and climate data to eight of the most energy-intensive states in the U.S.A. Using both a primitive (temperature) variable approach and a derived (degree day) one they prove the existence of a relationship between temperature and electricity consumption. More specifically they find that the primitive variable approach is as good as the degree-day models for natural gas whereas, for electricity, the derived variable approach is the best one. This is due to the fact that natural gas is used in space heating applications only and a single temperature parameter, either heating degree-days or the primitive variable of temperature is satisfactory. Electricity is used both for heating and cooling applications and only the introduction of two independent indicators (heating and cooling degree-days), can take the dependence of electricity consumption on temperature properly into consideration. They also find that temperature is the most significant weather factor explaining electricity and gas demand.
Valor, Meneu and Caselles (2000) analyse the relationship between electricity load and daily air temperature in Spain. Using daily electricity load from 1983 through 1999, they find that electricity demand shows a significant trend related to socio-economic and demographic factors, to seasonal effects unrelated to weather conditions (weekly and holiday effects) and to other factors related to temperature (monthly effects). The observed relation between temperature and electricity demand is non-linear with regions of non-sensitivity (around 18 degree Celsius) and regions with high sensitivity. They found that the use of temperature derived variables, such as the heating degree and the cooling degree-day variables, allows a better characterisation and quantification of the electricity demand functions. Finally, the use of climate variables shows that the sensitivity of electricity load to daily air temperature has increased over time, to a higher degree in Summer than in Winter.

Pardo, Meneu and Valor (2002) examine the relationship between the Spanish daily electricity demand and derived weather variables, such as heating and cooling degree-days. Using different statistical models they find clear evidence of the existence of a relation between climate and temperature. Such a relation shows an important daily and monthly seasonal structure. The authors focus on the analysis of the consequences of serial correlation and of the autoregressive behaviour of the weather variables in the demand estimation. In this regard they find that Spanish electricity is affected by current as well as by previous temperatures and the model obtained using lagged temperatures variables, specially heating degree-days, has the higher predictive power.

3. Data Description

The data used in this analysis related to gas consumption data and weather data in Milan and Palermo.

We chose to investigate the relation between gas consumption in Milan and Palermo because they represent in a significant way the heterogeneous Italian climatic subregions. Milan is the most populated city in the North of Italy. Palermo is one of the most important cities in the south of Italy. They are both big cities with composite energy demand. We believe that, given the existence of very different climatic regions in Italy, such an approach is preferable to a national aggregated analysis in order to reveal the true impact of different weather conditions on gas consumption.

Gas Data

The gas data are daily gas consumption, G_t, (given in m^3) in Palermo and Milan. The Palermo data go from January 1994 to December 2000. The Milan time series goes from January 1997 to December 2000. The data refer to all economics sectors (residential, commercial, and industrial). We apply the natural logarithm of all values (LG_t) in order to avoid non-stationarity effects for the time series. Figure 3 and 4 show the gas load evolution in Palermo over the period of time considered.

Figure 3 : Palermo Gas Load Evolution

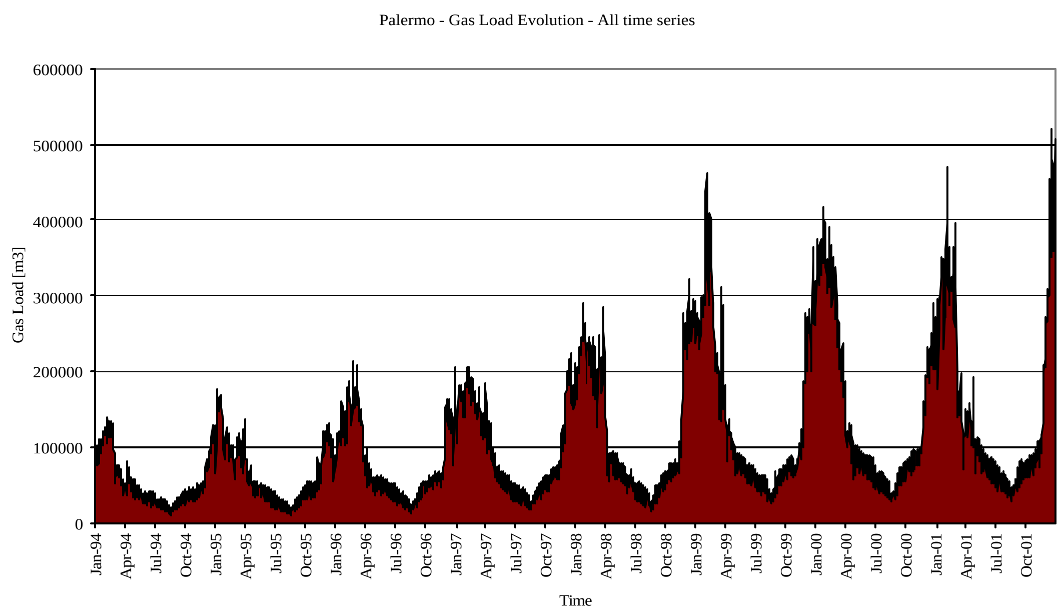
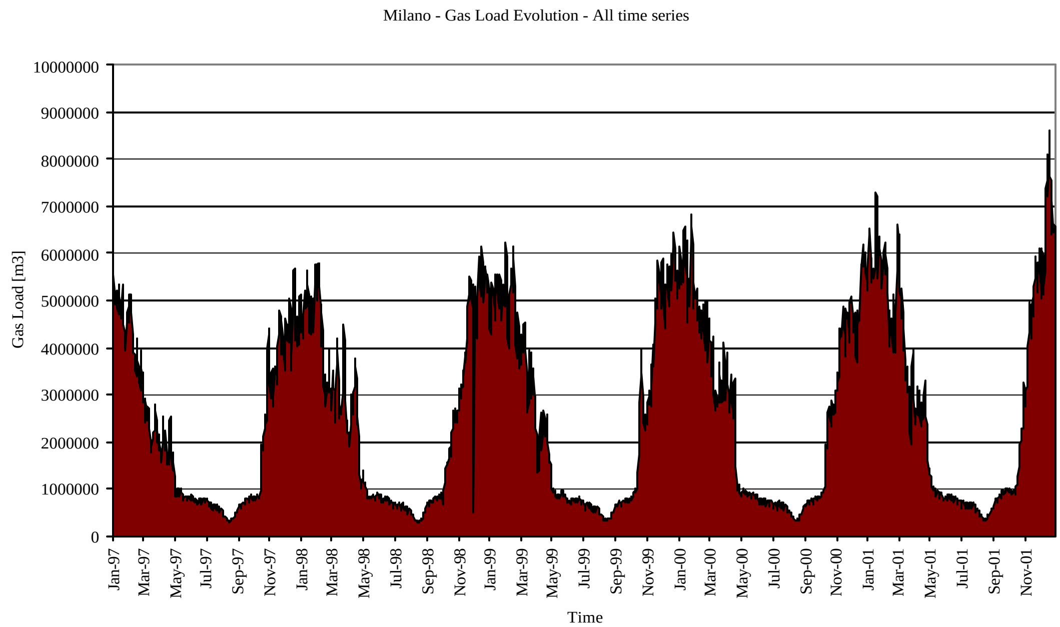


Figure 4 : Milano gas load evolution



Weather Data

As in the case of gas consumption data, the weather data are represented by two different sets of data: the Palermo one and the Milan one. The Palermo weather database includes daily maximum and minimum temperatures (in degree Celsius), daily relative mean humidity (in percentage points), daily mean pressure (in mill bar at 0^0 C) and daily rain levels (in millimetres). The Milan database include daily maximum (T_{max}) and minimum temperature (T_{min}). In both cases, the arithmetic mean daily temperature, $T_{avg} = (T_{min} + T_{max})/2$, has been chosen as the main temperature variable, because it represents the temperature evolution within a day well.

Figure 5 and tables 1 and 2 provide statistical information on the data used. According to the critical values of skewness and kurtosis (respectively 0 and 3), both the energy consumption and the weather variables appear to be far from a Gaussian distribution.

Covariance structure analysis is used for inference and for dimension reduction with multivariate data. When data are not normally distributed, the asymptotic distribution free (ADF) method is often used to fit a proposed model. The ADF test statistic is asymptotically distributed as a chi-square variable. Experience with real data indicates that the ADF statistic tends to reject theoretically meaningful models. Empirical simulation shows that the ADF statistic rejects correct models too often for all but impractically large sample sizes. By comparing mean and covariance structure analysis with its analogue in the multivariate linear model, we propose some modified ADF test statistics whose distributions are approximated by F distributions. Empirical studies show that the distributions of the new statistics are more closely approximated by F distributions than are the original ADF statistics when referred to chi-square distributions. Detailed analysis indicates why the ADF statistic fails on large models and why F tests and corrections give better results.

While it may appear that the test can be carried out by performing a t-test on the estimated, the t-statistic under the null hypothesis of a unit root does not have the conventional t-distribution. Dickey and Fuller (1979) showed that the distribution under the null hypothesis is non-standard, and simulated the critical values for selected sample sizes. MacKinnon (1991) has implemented a much larger set of simula tions than those tabulated by Dickey and Fuller. In addition, MacKinnon estimates the response surface using the simulation results, permitting the calculation of Dickey-Fuller critical values for any sample size and for any number of right-hand variables.
In Table 2 we show the outcomes such as the Akaike information criterion and the usual variance tests estimated for an autoregressive equation at the fourth degree.

Table 1 – Normality statistics of weather and energy consumption in Milan and Palermo

	MILAN			PALERMO		
	GAS	**TEMP**	**PRES**	**GAS**	**TEMP**	**PRES**
Skewness	0.5703	-0.0908	0.6460	1.5768	0.1206	-0.5588
Kurtosis	1.9604	1.7710	1.9998	5.0540	2.0685	4.4304
Jarque-Bera[7]	181.2099	117.4296	203.1421	1508.765	98.6463	351.0634
Probability	0.0000	0.0000	0.0000	0.000	0.0000	0.0000

[7] The Jarque-Bera test depends directly upon skewness and kurtosis; it is useful for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The statistic is computed as:

$$\mathbf{JB} = \frac{\mathbf{N} - k}{\mathbf{6}} \bullet \left[\mathbf{S}^2 + \frac{\mathbf{1}}{\mathbf{4}}(\mathbf{K} - \mathbf{3})^2\right]$$

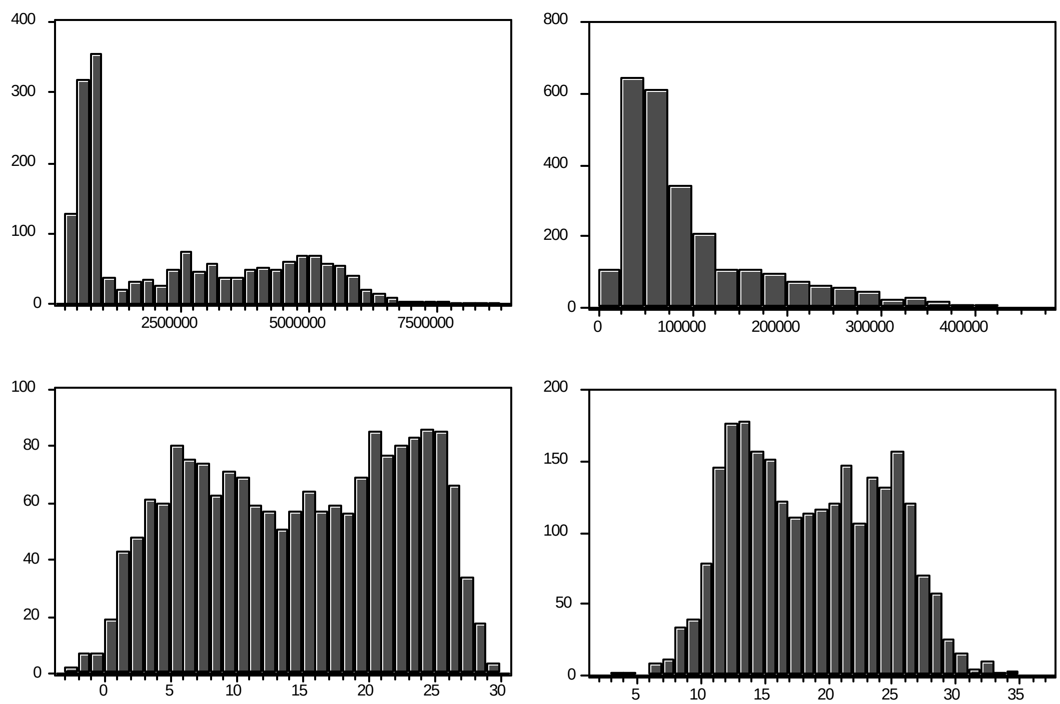
where S is the skewness, K is the kurtosis, and k represents the number of estimated coefficients used to create the series.

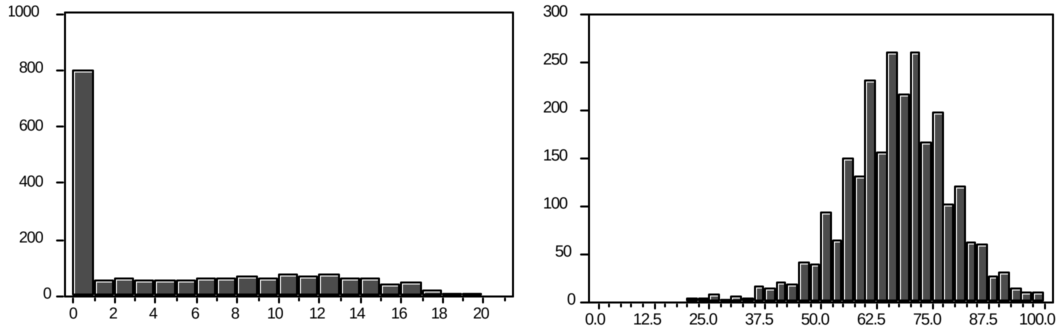
Table 2 – Fourth degree autoregressive tests of weather and energy consumption in Milan and Palermo

	MILAN			PALERMO		
	GAS	**TEMP**	**PRES**	**GAS**	**TEMP**	**PRES**
ADF Test Statistic	-2.399	-3.518	-3.930	-14.860	-5.291	-14.860
Akaike info criterion	28.218	4.002	3.622	7.486	4.073	7.486
Adjusted R-squared	0.031	0.042	0.060	0.238	0.072	0.238
Durbin-Watson stat	2.017	2.009	2.006	1.996	2.018	1.996

Figure 5 – Data Distribution (Gas; Temperature; Pressure)

MILAN. Data Distribution	**PALERMO. Data Distribution**





Since the critical values proposed by MacKinnon for the rejection of a hypothesis of a unit root generally depend on probability levels such as 1% (-3.4435), 5% (-2.8666) and 10% (-2.5695), the empirical values appear to be interesting, except for the case of gas time series in Milan. Very low appear to be the adjusted R-squared, whose higher value is 23.8 per cent in the case of gas in Palermo. Finally, the Durbin-Watson statistics are generally close to the critical value of 2, representative of the absence of negative or positive autocorrelation.

4. Methodology and Results

The analysis has been structured following a stepwise scheme. We started with the simplest model and we progressively added new terms in order to assess separately the impact of different factors on daily gas consumption. We performed linear regressions using the least square method. This procedure is used in Engle (1992), Peirson and Henley (1994), Pardo-Menue and Valor (2002). The analysis is first performed for the Palermo data and afterwards for the Milan one. In the Milan case we directly tested our last model.

The first model investigates the relation between gas demand (LG) and a set of weather variables such as average temperature (T_{avgt}), humidity (H_t), pressure (P_t) and rain (R_t). The model is given by the following expression

$$LG = c + aT_{avg\,t} + bH_t + gR_t + dP_t + e_t \qquad [1]$$

The results of equation [1] estimation are given in table 3. All the variables are statistically significant except for the rain variable *(R_t)*. The relationship between gas consumption and mean temperature is negative as expected, and statistically significant. As temperature decreases gas consumption increases. The humidity variable has a statistically significant negative sign. The pressure variable has a positive significant sign. Other studies conducted for different countries suggest that temperature is the relevant weather variable in explaining gas consumption and that other variables are not statistically significant. In our model humidity and pressure seems to be important. The R^2 is higher than 50% (ca 66%), which can be considered a good but not yet completely satisfactory level.

Table 3 - Model one estimation results (Palermo)

Variable	Coefficient	t Statistic	Pr > t
c	8.00405	5.14	<.0001
$T_{avg\ t}$	-0.1028	-59.44	<.0001
Ht	-0.00452	-6.00	<.0001
Rt	0.00281	1.73	0.0832
Pt	0.00727	3.56	0.0004
R-squared	0.6671		
Adjusted R-squared	0.6666		

One of the reasons for a relative low R^2, could be related to the existence of a non linear relation between gas consumption and temperature. Figure 6 shows the scatter plot of gas consumption and mean temperature. As expected gas demand sharply increases when temperature falls below eighteen degrees. There is a "neutral zone" around 18^0 C, where the gas demand is inelastic to weather conditions. Even on the hottest days, there is always some demand for gas. This is a "base level" due to the demand for activities such as cooking. In general, gas demand has a maximum in Winter time and a minimum in Summer time. In order to better capture this non linear and inelastic behaviour of gas demand, we defined a derived temperature variable, the Heating Degree Days function. The Heating Degree Days is calculated as follows:

$$HDD = \max (18^0 C - T_{avgt}; 0) \qquad [2]$$

For the Summer season, cooling degree days function is defined as the equation [3] shows.

$$CDD = \max (T_{avg}t - 18^0 C; 0) \qquad [3]$$

The Heating Degree Day function has a positive value if temperature falls below eighteen degrees and zero otherwise. Appendix gives provides descriptive values of HDD and CDD for both Milan and Palermo.

Based on these considerations, model two regresses the gas demand over the same set of weather variable like model one except for the temperature where we used the HDD derived temperature variable.

$$LG = c + aHDD_t + bH_t + gR_t + dP_t + e_t \qquad [4]$$

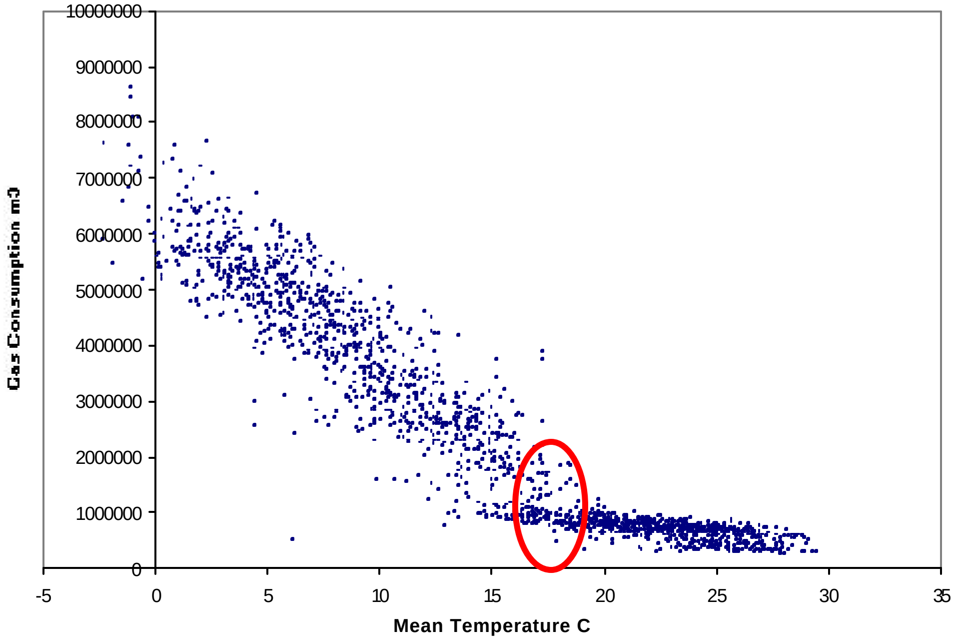
Table 4 shows equation [4] estimation results. The HDDt variable has a positive and significant value. As expected, as temperature decreases the HDDt variable increases and gas consumption increases as well. The estimated coefficient shows a higher absolute value in comparison with the value of mean temperature from model one and it might suggest that the use of a derived variable for temperature is useful in order to achieve better statistical results. Among the other variables, only the pressure variable is now significant. However the R^2 is lower than in the previous model.

Table 4 - Model two estimation results (Palermo)

Variable	Coefficient	T Statistic	Pr > t
c	1.57758	-0.98	0.3283
HDDt	0.192	52.45	<.0001
Ht	0.00078522	0.99	0.3207
R_t	0.00337	1.93	0.0532
P_t	0.01638	7.65	<.0001
R-Square	0.6166		
Adj R-Square	0.6160		
Durbin-Watson stat	0.22723		

The low R^2 could be related to the presence of lagged effect of the weather variables on the gas demand. There are several reasons that suggest an influence of past weather variables on the present gas demand. First of all the thermal insulation of buildings could operate as a barrier between indoor and outdoor temperature. If so we could notice a lagged adjustment of gas consumption to temperature. Second, residential consumption could be adjusted with lags to temperature changes. In order to take these observations into consideration we expanded model two by adding lagged weather variables.

Figure 6 - Total daily gas consumption and mean temperature



Taking into consideration the fact that lagged effects are relevant only on short term periods we added delayed variables up to two days. Model three is so given by the equation [5]

$$\boldsymbol{LG} = \boldsymbol{c} + \alpha_0 \boldsymbol{HDD_t} + \alpha_1 \boldsymbol{HDD_{t-1}} + \alpha_2 \boldsymbol{HDD_{t-2}} + \beta_0 \boldsymbol{H_t} + \beta_1 \boldsymbol{H_{t-1}} + \beta_2 \boldsymbol{H_{t-2}} + \gamma_0 \boldsymbol{R_t} + \gamma_1 \boldsymbol{R_{t-1}} + \gamma_2 \boldsymbol{R_{t-2}} + \delta_0 \boldsymbol{P_t} + \delta_1 \boldsymbol{P_{t-1}} + \delta_2 \boldsymbol{P_{t-2}} + \varepsilon_t \qquad [5]$$

The estimation outcomes are reported in table 5. Given these results it is possible to reach some interesting conclusions:

- The HDDt variable is significant up to a delay of two days;
- The other climatic variables are not statistically significant ;

Table 5 - Model three estimation outcomes (Palermo)

Variable	Coefficient	t-Statistic	Pr > t
c	-9.583414	-5.551060	0.0000
HDD_t	0.106124	12.74788	0.0000
HDD_{t-1}	0.029819	2.702715	0.0069
HDD_{t-2}	0.057121	6.828582	0.0000
Ht	0.000916	0.969963	0.3322
H_{t-1}	0.001030	0.961191	0.3366
H_{t-2}	0.001756	1.881945	0.0600
R_t	0.001173	0.776472	0.4376
R_{t-1}	-0.000158	-0.104242	0.9170
R_{t-2}	-0.001225	-0.817465	0.4138
P_t	0.007407	2.198998	0.0280
P_{t-1}	-0.005463	-1.166371	0.2436
P_{t-2}	0.024892	7.341890	0.0000
R-squared	0.721009		
Adjusted R-squared	0.719212		
Durbin-Watson stat	0.297962		

The R^2 value slightly increases if compared with the previous model but is still not satisfactory. One possible reason could be the presence of seasonal pattern on the demand. The existence of monthly seasonal patterns on gas demand has been proved by many previous studies. Figures three and four suggest that this conclusion is true both in Palermo (figure 5) and Milan (figure 6) cases. The figures show the Monthly seasonal variation index over the whole period defined as follows:

$$MSVI_{ij} = \frac{M_{ij}}{M_j} \qquad [6]$$

where $MSVI_{ij}$ is the index value for month i in year j, M_{ij} is the monthly gas consumption for month i in year j and M_j is the monthly average gas consumption for year j. For the Palermo data it is possible to notice that the maximum consumption is in December with a reduction in Spring and Autumn months and a minimum in August. The Milan dataset shows a similar pattern with a maximum in December and January, a reduction in the Spring months up to the minimum of August and a new increase in Autumn. The MSVI in Milan is higher than in Palermo. In order to consider an eventual monthly seasonality not related to temperature we introduced to our model a set of eleven dummy variables, M_{jt}, each one representing a month in a year. M_{jt} is equal to 1 if the t observation belong to month j and 0 otherwise. The base month is January.
Other than a monthly pattern, gas consumption usually exhibits a daily pattern as well. Figures 7 and 8 show the daily seasonal variation index for Palermo and Milan. This index is defined as:

$$\boldsymbol{DSVI_{ijk} = \frac{D_{ijk}}{D_{jk}}} \qquad [7]$$

where $DSVI_{ikj}$ is the index value for day i in week j of year k, D_{ijk} is the daily gas consumption for day i in week j of year k and D_{jk} is the daily average gas consumption in week j of year k. In both cases it is possible to recognise a weekend effect. The average daily seasonal variation index, in fact, decreases on Saturday and Sunday. The effect is stronger in Palermo than in Milan. In order to consider this effect we add to our model a set of 6 dummy variables (W_{it}) representing the day of the week. W_{it} is equal to 1 if observation t belongs to day i and 0 otherwise.

Figure 7 - Monthly seasonal variation index in Palermo

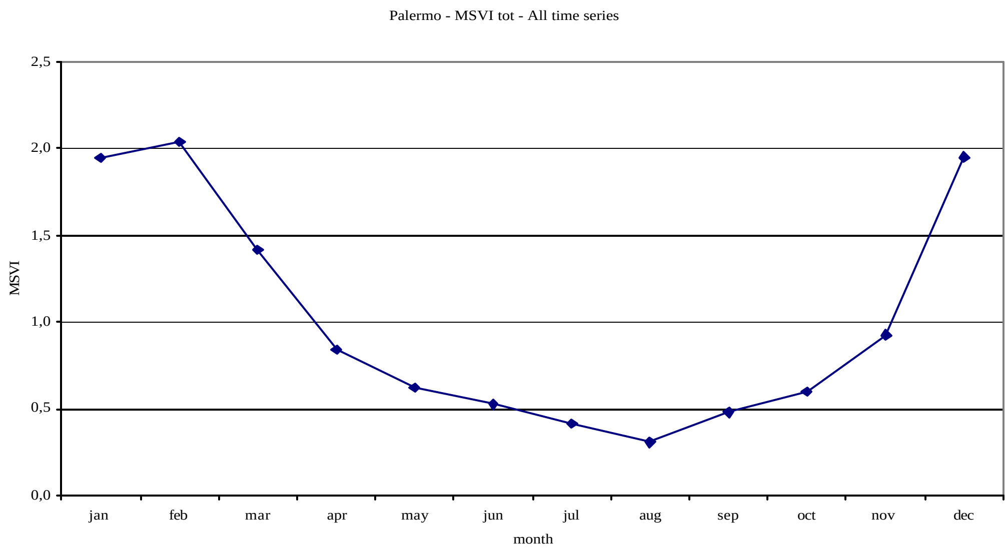


Figure 8 - Monthly seasonal variation index in Milano

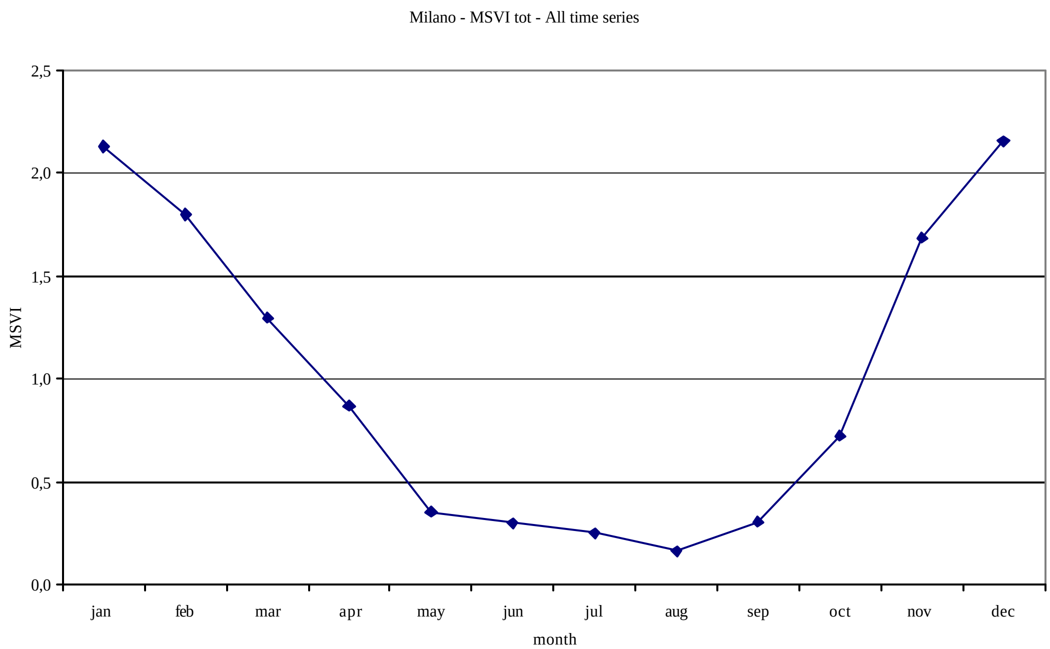


Figure 9 - Daily seasonal variation index (Palermo)

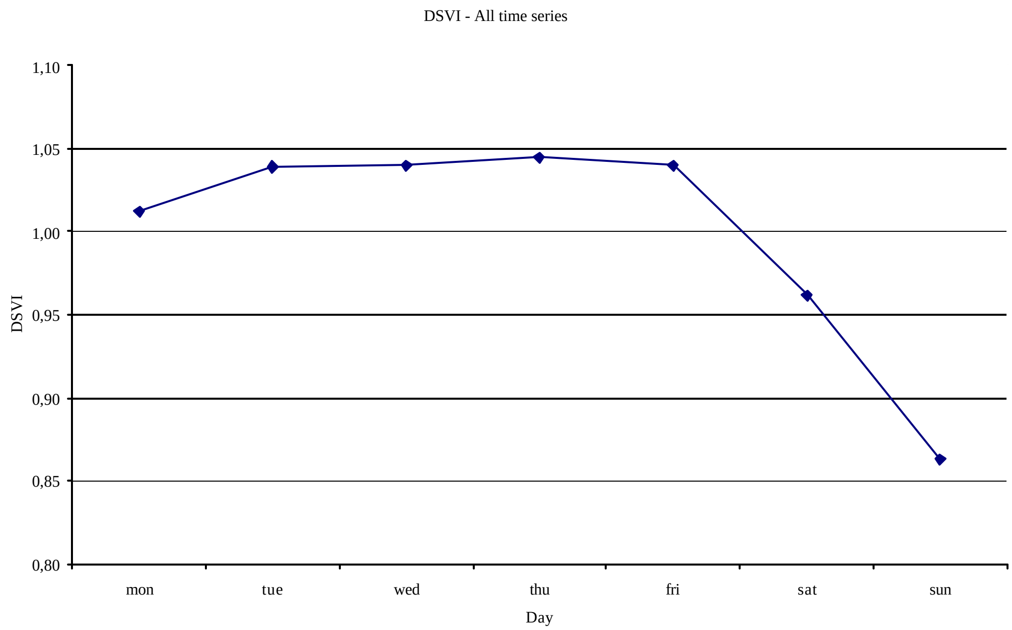
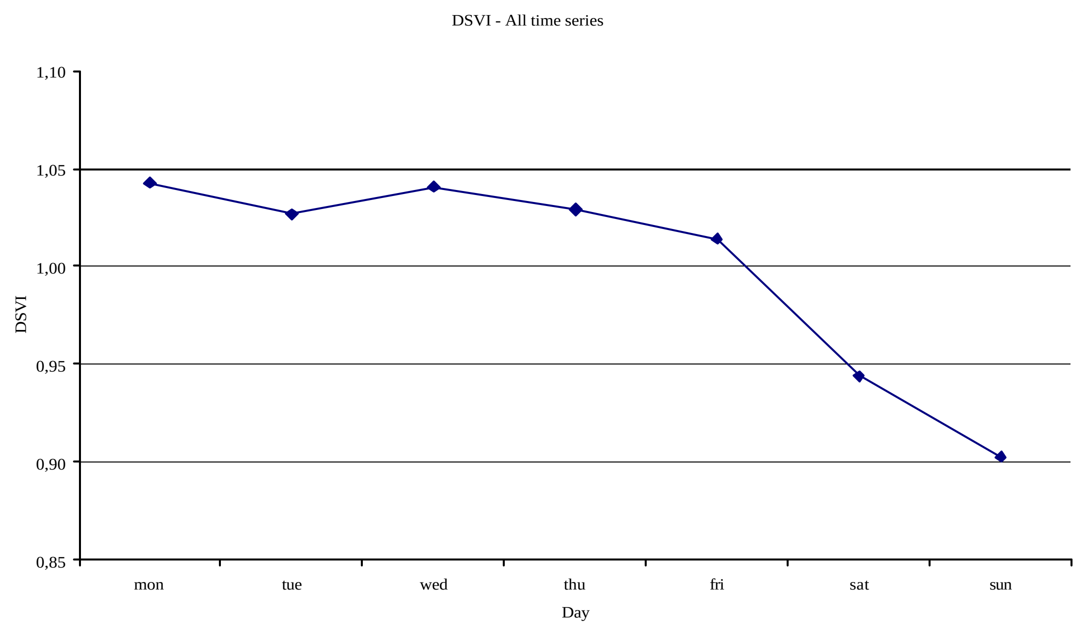


Figure 10 - Daily seasonal variation index (Milan)



Finally, in order to consider the eventual presence of a holiday effect, that is a reduction in gas consumption during vacations and public holidays, we introduce in model four a holiday dummy variable (F_t).This dummy variable is equal to one if observation t is in a holiday day and 0 if not. Model four is then given by:

$$LG = c + a_0 HDD_t + a_1 HDD_{t-1} + a_2 HDD_{t-2} + b_0 H_t + b_1 H_{t-1} + \\ b_2 H_{t-2} + g_0 R_t + g_1 R_{t-1} + g_2 R_{t-2} + d_0 P_t + d_1 P_{t-1} + d_2 P_{t-2} + F_t + \sum_{i=2}^{7} g_i W_{it} + \sum_{i=2}^{12} J_i M_{it} + e_t \quad [8]$$

This means that, for example, the gas demand on a non-holiday Tuesday in January would be equal to:

$$LG = c + a_0 HDD_t + a_1 HDD_{t-1} + a_2 HDD_{t-2} + b_0 H_t + b_1 H_{t-1} + \\ b_2 H_{t-2} + g_0 R_t + g_1 R_{t-1} + g_2 R_{t-2} + d_0 P_t + d_1 P_{t-1} + d_2 P_{t-2} + g_1 \quad [9]$$

The gas demand on a non holiday Tuesday in February would be:

$$LG = c + a_0 HDD_t + a_1 HDD_{t-1} + a_2 HDD_{t-2} + b_0 H_t + b_1 H_{t-1} + \\ b_2 H_{t-2} + g_0 R_t + g_1 R_{t-1} + g_2 R_{t-2} + d_0 P_t + d_1 P_{t-1} + d_2 P_{t-2} + g_1 + J_1 \quad [10]$$

The results of the model estimation are given on table 6. The relevance of the seasonality effects on gas consumption is revealed by the extraordinary improvement of R^2 now equal to more than 80%. The heating degree days variable, either present or lagged, improves their significance. The humidity and pressure variable are not significant. The rain variable has a positive significant coefficient. The dummies representing the days of the week are positive and not significant, except for the Saturday and Sunday dummies that have a negative significant sign. This goes along with our expectation of a reduction in gas consumption during weekends. The dummies related to the monthly seasonality are all negative, except for December. As expected it is possible to observe a decrease of value from February to July, an increase from September to December, and a minimum value in August. This means that usually the gas consumption grows during Autumn and decreases in Spring. The holiday dummy is negative and significant, as expected.

Table 6 - Model four estimation results (Palermo)

Variable	*Coefficient*	*t-Statistic*	*Prob.*
c	-2.421094	-1.921691	0.0548
HDD_t	0.051837	8.412310	0.0000
HDD_{t-1}	0.015785	2.023789	0.0431
HDD_{t-2}	0.022865	3.743984	0.0002
Hat	-0.000316	-0.473111	0.6362
H_{t-1}	2.36E-05	0.031178	0.9751
H_{t-2}	-0.000758	-1.143119	0.2531
R_t	0.001847	1.723180	0.0850
R_{t-1}	0.001453	1.354419	0.1758
R_{t-2}	0.001339	1.255383	0.2095
P_t	0.008166	3.424625	0.0006
P_{t-1}	-0.002641	-0.800144	0.4237
P_{t-2}	0.013263	5.499181	0.0000
F_t ***(Holiday)***	-0.255518	-6.015470	0.0000
W_2 ***(Tuesday)***	0.041395	1.804318	0.0713
W_3 ***(Wednesday)***	0.043031	1.878929	0.0604
W_4 ***(Thursday)***	0.045064	1.961594	0.0500
W_5***(Friday)***	0.037602	1.639175	0.1013
W_6 ***(Saturday)***	-0.065076	-2.837296	0.0046
W_7 ***(Sunday)***	-0.244954	-10.68961	0.0000
M_2 ***(February)***	-0.020780	-0.665174	0.5060
M_3 ***(March)***	-0.144402	-4.713580	0.0000
M_4 ***(April)***	-0.491978	-14.47592	0.0000
M_5 ***(May)***	-0.557639	-14.28469	0.0000
M_6 ***(June)***	-0.731912	-18.17022	0.0000
M_7 ***(July)***	-0.951817	-23.66037	0.0000
M_8 ***(August)***	-1.252293	-30.77019	0.0000
M_9 ***(September)***	-0.871553	-21.98485	0.0000
M_{10} ***(October)***	-0.686485	-17.59485	0.0000
M_{11} ***(November)***	-0.491560	-14.03672	0.0000
M_{12} ***(December)***	0.162009	4.914343	0.0000
R-squared	0.863291		
Adjusted R-squared	0.861068		
Durbin-Watson stat	0.221661		

In order to further improve the significance of our model we finally took into consideration serial correlation. In previous models, in fact, the Durbin Watson test was quite low suggesting the existence of autocorrelation in the error term. To reduce such a correlation we introduced in our model a second order autoregressive structure in the error term:

$$(1-\varphi_1 L-\varphi_2 L^2)\varepsilon_t=\varsigma_t \qquad [11]$$

We removed all the weather variables other than temperature because they were not statistically significant. Furthermore, since all the day dummies variables in the previous model were not significant except for the weekend ones, we eliminated the 6-day dummies variables and we introduced a weekend dummy (W_t). W_t is equal to 1 if observation t belongs to a weekend day

and 0 otherwise. Finally we did not consider the monthly dummies variables because in the new model with autoregressive structure in the error term they are no longer significant.
The final model is:

$$LG = c + \alpha_0 HDD_t + \alpha_1 HDD_{t-1} + \alpha_2 HDD_{t-2} + F_t + W_t + \varepsilon_t \qquad [12]$$

Table 7 gives the coefficient estimation for the final model. The R^2 is now equal to 96,77% a very satisfactory level. All the variables are significant. The HDD variable has the positive expected sign. The estimated coefficient decreases over time. This could indicate a more relevant importance of present effects rather than lagged effects. The holiday as well as the weekend dummies have a negative sign that is, as expected, gas demand decrease during holiday and weekend days.

Table 7 - Model five estimation results (Palermo)

Variable	Coefficient	t-Statistic	Prob.
C	11.21998	64.90907	0.0000
HDD_t	0.034343	16.00746	0.0000
HDD_t (lag 1)	0.007003	3.196813	0.0014
HDD_t (lag 2)	0.008608	4.014989	0.0001
Dummy "Holiday"	-0.181998	-37.36436	0.0000
Dummy "Weekend"	-0.183413	-13.59184	0.0000
AR(1)	0.639377	32.17243	0.0000
AR(2)	0.345698	17.41721	0.0000
R-squared	0.967735		
Adjusted R-squared	0.967646		
Durbin-Watson stat	2.138747		

We repeated the same regression for the Milan data. The results of the various models are approximately the same. We report here just the final model coefficient estimation. The model has a very good explicative capability (R^2 more than 99%). All the estimated coefficients are statistically significant and with the expected sign.

Table 8 - Model five estimation results (Milan)

Variable	Coefficient	t-Statistic	Prob.
C	13.73095	10.96920	0.0000
***HDD**$_t$*	0.025500	17.00303	0.0000
HDD**$_t$ **(lag 1)	0.007164	4.856694	0.0000
HDD**$_t$ **(lag 2)	0.005769	3.852987	0.0001
Dummy "Holiday"	-0.078751	-6.917407	0.0000
Dummy "Weekend"	-0.123602	-31.42912	0.0000
AR(1)	0.838467	35.19806	0.0000
AR(2)	0.159852	6.712210	0.0000
R-squared	0.997162		
Adjusted R-squared	0.997151		
Durbin-Watson stat	2.021638		

5. Weather risk and hedging strategy

The econometric analysis and the investigation of the existence of a relation between weather events and gas consumption are the first step to access a valuable hedging strategy. The hedging policy should in fact be based on the valuation of hedging costs compared to financial discomfort caused by weather events. This turns on estimating which weather conditions may seriously affect the business and measuring the costs of past adverse weather events into present financial terms. In this section we show how temperature risk may affect the revenues of a hypothetical gas company (MILGAS) based in Milan. Then we describe how weather derivatives contract may be used in order to allow our company to prevent unnecessary losses during adverse weather events.

Milgas is a gas distributor company operating in Milan. The average quantity of natural gas sold during the 1997-2001 period by the firm has been equal to 917,128,430.27 m3 leading to an average annual revenue of 229,282,107.57 €. Average annual standard deviation of consumption, equal to 4% in 1997 –2001 period, has increased up to a maximum of 10% during the last years.

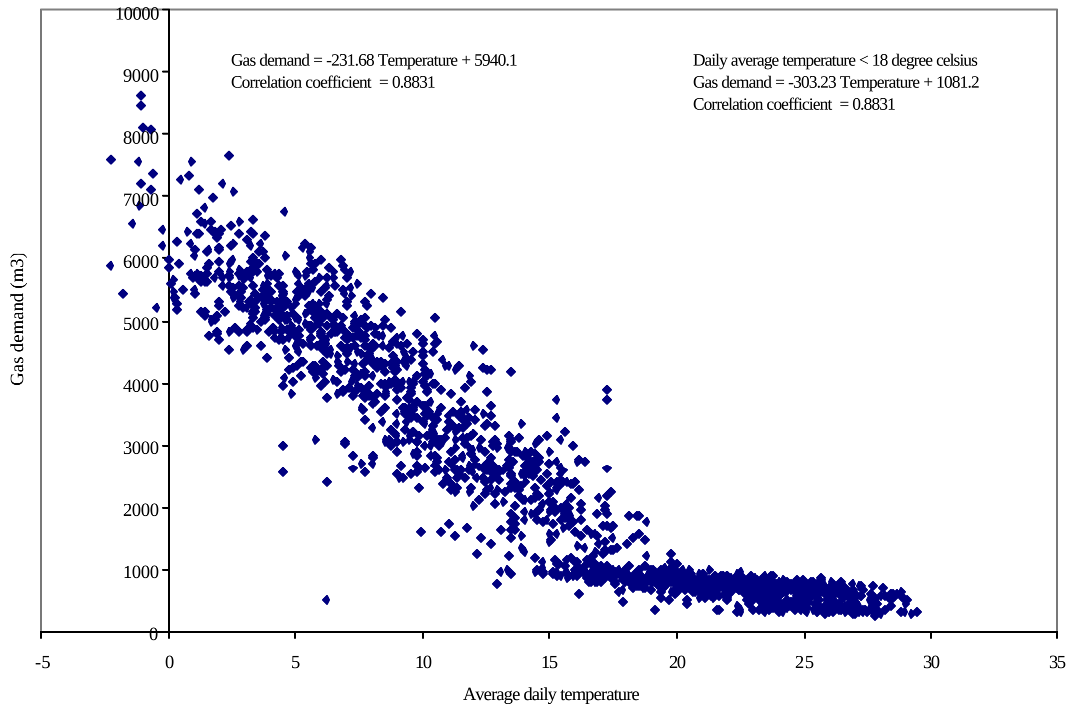
In the previous section we have proved the existence of a relation between temperature and gas consumption both in Palermo and in Milan. In this section we want to investigate the relation between Milan temperature and Milgas demand in order to quantify the impact of a weather change into its revenues.

Figure 11 shows the relation between average daily temperature and daily company demand. The figure shows that, as proved in previous section, gas demand and temperature are strongly negative correlated (-0.88). During the whole year, the average temperature in Milan is around 15 °C with a standard deviation of 7.99[8]. As far as the demand is concerned, the yearly average of gas sold is equal to 917,128,430 m3, as already stated, whereas the yearly average demand based only on colder days is 803,098,143.28 m3 with a standard deviation of 41%. In this analysis we consider as colder period the days between 1 of January and 30 of April and

[8] See Appendix for further details.

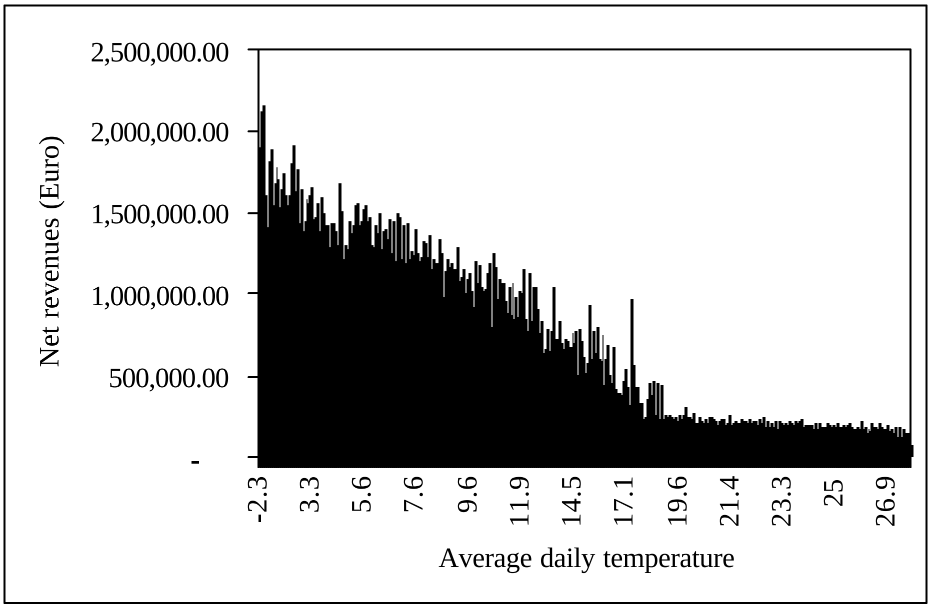
between the 1 of October and the 31 of December each year. In this period the average temperature in Milan is around 9°C and the standard deviation is equal to 4.35°C. This is approximately the year time when gas is used for residential heating. Demand appears to be strongly concentrated during the cold period (88% of the yearly total demand). The amount of gas that Milgas sells during winter months is very dependent on temperature and, as a consequence, revenues are very volatile. Figure 9 shows that the company has also a base level of gas demand (12% of yearly total demand). This base level is related to activities such as domestic cooking, fuelling hot water heaters and industrial consumption of natural gas as row material. This component is pretty stable during the different years. Winter is therefore the period of the year where the company has its greatest exposure to reduced deliveries due to actual temperature different from the expected one.

Figure 11: Relation between temperature and Milgas demand



The price that Milgas charges to its customers is the sum of a fix component and a variable one. The fixed component is determined and under the control of the local authority. The variable component is settled by the company and, considered the lack of real competition in the local gas market, it is changed in order to allow the company to reach the targeted profits. The company hedges the price risk, strictly related to the fixed component of the price, through forward contracts settled at the beginning of each year. This doesn't hedge weather risk. In fact, if the number of HDDS forecasted is not achieved, the company will not realise the target profits due to actual gas consumption different from the predicted one. If the number of HDDs is higher then forecasted (this happen in a colder than usual winter) the gas demand could exceed the planned one and additional amounts of gas must be bought on the spot market in order to satisfy clients needs. This is a risk because the gas price on the spot market during high demand period will probably be higher than the contractual selling price. On the other side, if the amount of HDDs is lower then forecasted, a lower quantity of gas will be delivered and this will turn in reduced revenues. The temperature risk may be therefore linked both to warmer and colder than normal winter. Figure 12 shows the relation between daily temperature and revenues, which increase as long as temperature decreases and the company seems to be negatively affected only by warmer than normal winters. A possible explanation to this could be related to the under examination period of temperature distribution in Milan where, in fact, warmer winters have a high likelihood than colder winters.

Figure 12: Relation between temperature and Milgas net revenues



Looking again to Figure 11, it's possible to measure Milgas financial exposure to weather risk. Given the estimated relation between temperature and gas that is:

Gas (m^3) = 303,226 temperature (°C) + 7* 10^6

and the net price of gas that is 0,25€/m^3, Milgas financial exposure is approximately equal to 75.000 €/°C. We then turn to consider the temperature distribution in Milan during colder months and measured the probability of different temperature. This lead us to conclude that the company maximum exposition to weather risk is around 10,000,000 euros..

Once measured financial exposure, the last step of a hedging strategy is to consider costs and benefits of different hedging instruments. In section four we explained why HDDs more than temperature is the underlying of weather contracts. Since the hedging final objective is to stabilise seasonal more than daily revenues, cumulative heating degree days (CHDDs) are a suitable variable than heating degree days.

There is at least three hedging alternatives available to cover Milgas risk. The first one is an HDD swap with a tick size equal to the company financial exposure, that is €.75.000, and a strike level equal to 2196 CHDDs, that is the annual average CHDDs in Milan. In case of a winter temperature on average with the historical mean, the swap cash flows will be zero. In case of a milder winter, the company will receive positive cash flows equal to the difference between the actual CDDs and the swap rate (2196) multiplied by the tick size. Vice versa, in case of a colder winter Milgas will have to pay the counterpart the difference between the swap rate and the actual CHDDS multiplied by 75.081 €. This contract allows profit stabilisation but enables to have benefits from colder than average winter.

As an alternative, the company could consider a CHDD put option. In this case it receives a positive cash flows in case of a warmer winter but could benefits of cold winter. One of the main problem on using option to hedge risk is their cost that is inversely related to the strike level. There is a trade off between option premium and option payoff. The strike of the option could be chosen based on winter forecast at the beginning of the season. That is, if the seasonal forecast are for a cold winter the strike of the option could be fixed to a level equal to the mean CHDDS plus the CHDDs standard deviation so to minimise the hedging costs. Vice-versa if forecasts are for a warmer than normal winter the strike could be fixed at a level equal to the historical CHDDs mean less their standard deviation. In this case the higher premium of the option should be compensated, if forecasts are correct, by higher payoff.

The last alternative could be a CHDDs collar that is the combination of a low strike put bought and a higher strike put sold. In this case Milgas will receive a positive payment if the actual CHDDs will be lower than the bought put strike and will have to make a payment if the actual CHDDS will be higher than the sold put option strike. This would allow the company to benefits of colder than normal winter up to the higher strike and to receive positive cashflows in case of warmer than lower strike winters. A maximum revenue is fixed as long as a minimum revenue, leaving an area of profits variability only in behind the two strike.

Conclusions

In this paper an attempt was made to determine whether statistical models may be appropriate to estimate a relation between weather variables and energy consumption, in order to evaluate the potential demand for hedging contracts.
The results seem to indicate that, in the 1994-2000 period for Palermo and 1997-2000 for Milan, among the explicative variables, the most significant is the temperature, both coincident and lagged. As expected, the seasonality component is particularly high: once implemented into the regression, the R^2 improves from 70 per cent to roughly 80 per cent. The monthly and daily patterns detected for the two datasets show parabolic and negative slope, respectively. On balance, humidity and pressure do not seem to be statistically significant.
These findings may be useful to assess the relation between weather derivatives and underlying, so to point up the interest for these financial instruments from the market. We proved that weather risk might be very important to a gas distributor company whose revenues are really dependent on weather. We believe that many other sectors have a relevant exposure to weather risk. However most of the time companies do not hedge weather risk for two main reason.

Some time they underestimate the impact of weather on their business. Some other time they know the relevance of weather risk but traditional insurance contract are too expensive and weather derivatives, in the European market, are a new still not well know instruments. Our analysis shows that a development of weather derivatives market in Europe could help corporations to stabilise their profits.

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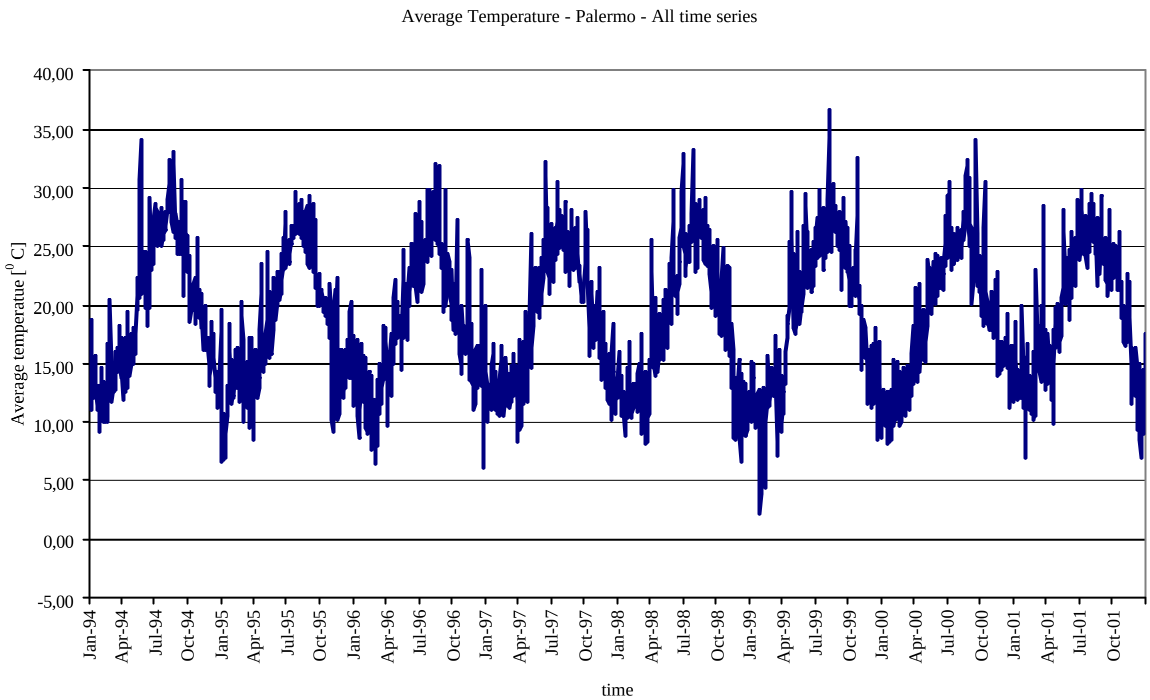
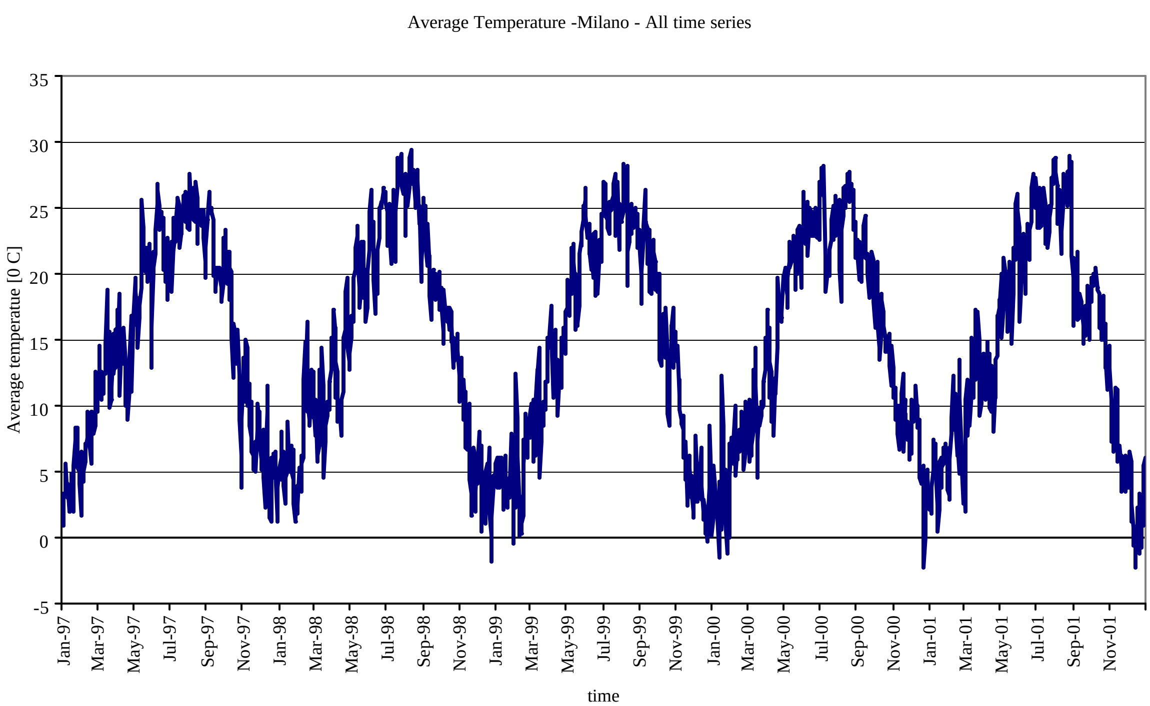
Appendix

Figure: Average Temperature – Palermo



Figure



		PALERMO		
Year	**MeanTavg**	**TmedSTDEV**	**Gas total load**	**Gas mean load**
1994	19,523	5,834	20328775	55695
1995	18,529	5,532	23631637	64744
1996	18,163	5,390	28782524	78641
1997	18,509	5,487	35079485	96108
1998	18,333	5,899	44789690	122711
1999	19,088	6,467	51067841	140296
2000	19,016	5,709	53601146	146451
2001	19,350	5,522	56357210	154403
All Time series	18,814	5,761	313876273	107418

			PALERMO			
Year	**Hdd Avg**	**HddS**	**Hdd STDEV**	**Cdd Avg**	**CddS**	**Cd**
1994	1,776	648,400	2,362	3,300	1204,400	
1995	2,112	771,000	2,803	2,641	964,050	
1996	2,170	794,050	2,902	2,333	853,750	
1997	2,190	799,180	2,643	2,698	984,900	
1998	2,446	892,900	3,016	2,779	1014,450	
1999	2,302	840,305	3,322	3,391	1237,550	
2000	1,970	720,900	2,745	2,986	1092,700	
2001	1,793	654,455	2,597	3,143	1147,165	
All Time series	2,095	6121,190	2,817	2,909	8498,965	

		MILANO		
Year	MeanTavg	TmedSTDEV	Gas total load	Gas mean load
1997	15,054	7,567	802263828	2204022
1998	14,888	8,134	879553615	2409736
1999	14,415	8,172	926623119	2538693
2000	15,029	7,849	942780269	2575902
2001	14,540	8,232	1031165641	2825111
All Time series	15,074	7,990	4582386472	2510897

			MILANO			
Year	Hdd Avg	HddS	Hdd STDEV	Cdd Avg	CddS	Cd
1997	4,954	1808,360	5,425	2,008	733,000	
1998	5,238	1911,900	5,724	2,126	776,150	
1999	5,562	2029,950	6,047	1,977	721,435	
2000	5,050	1848,250	5,645	2,087	764,000	
2001	5,426	1980,600	6,015	1,966	717,750	
All Time series	5,246	9579,060	5,774	2,033	3712,335	