CAN WEATHER DERIVATIVES BE IMPLEMENTED TO COVER VITICULTURE RELATED-RISKS? (REFEREED)

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Abstract

The management of weather-related risks is one of the main concerns of the farmers: the development of tools helping their risk covering of unfavourable climate seasons seems essential. This article is mainly focused on a financial contracts family: weather derivatives. The study tackles more specifically the wine-producing industry. The kind of weather-related risks the viticulturists are exposed to is first analyzed. The offer of weather derivatives which can be proposed by the market is also studied. A kind of product which can at the same time have a sufficient liquidity, and answer to the viticulturists needs, is inferred. In order to propose a pricing of these products, a simulation of the temperatures is realized. Determinist parameters of this simulation are estimated using an iterative method. Stochastic part is based on an autoregressive model with seasonal volatility, which parameters are estimated by the generalized least squares fitting method and which residual noise has been simulated by a numerical estimation of his inverse repartition function. The results of the study are presented for the products based on temperatures of Paris and Bordeaux.

Introduction

The agricultural sector is confronted as all economical sectors to numerous risks, but it presents the particularity to be very exposed to weather-related risks. Farms can be affected in a very short time by significant losses of harvest and can be faced with a critical financial situation. Because of this, the management of weather-related risks is one of the main concerns of the farmers: the development of tools helping their risk covering of unfavorable climate seasons seems essential. During the last decades, numerous agricultural insurance programs have been tested and developed in several countries. Nevertheless, their range of application is limited to risks presenting at least some insurability characteristics. Moreover, considering obtained results of their implementing, some authors are questioning their efficiency, and suggest reviewing the range and the use of such programs (J.Skees, 2001;

S.Makko, 2002). In this context, new complementary tools should be developed. This article is mainly focused on a financial contracts family: weather derivatives. The study tackles more specifically the wine-producing industry, for which a future market has already been created in France (Winefex).

The kind of weather-related risks the viticulturists are exposed to is first analyzed. The offer of weather derivatives which can be proposed by the market is also studied. A kind of products which can at the same time have a sufficient liquidity, and answer to the viticulturists needs, is inferred. In order to propose a pricing of these products, a simulation of temperatures is realized. Determinist parameters of this simulation are estimated using an iterative method. Stochastic part is based on an autoregressive model with seasonal volatility, which parameters are estimated by the generalized least squares fitting method and which residual noise has been simulated by a numerical estimation of his inverse repartition function. The results of the study are presented for the products based on temperatures of Paris and Bordeaux.

I. WEATHER-RELATED RISK IMPORTANCE FOR VITICULTURISTS

Wine industry is facing many risks, regarding mostly quality and yield. Both characteristics remain largely defined by weather conditions.

I.1. Weather-related risk and crop quality

Objective criteria generally used to estimate crop quality are sugar, polyphenols content and acidity, mostly determined by photosynthesis phenomenon. Photosynthesis phenomenon depends on three weather characteristics: temperature, sunshine and pluviometry.

Temperature is considered in France as the main limiting factor of photosynthesis. This factor influences crop quality mainly during grape maturation phase. Between 18°C and 33°C (64,4°F - 91,4°F), photosynthesis efficiency reaches 90 to 100% (Kliewer, 1970), optimum being achieved circus 25°C (77,00°F) (Alleweldt & Ruehl, 1993). This efficiency heavily decreases beyond these temperature limits. Therefore, two types of temperature conditions that may be prejudicial to crop quality should be considered: too low temperatures during the whole maturation period, that could result in insufficiently sugared or too acid grapes; too high temperatures, that could generate insufficiently acid crops, and that may force viticulturists to bring forward harvest, and to realize it when temperature are still high, which can be harmful to vinification process, specially for white wine. Specific vinification processes can correct some crop parameters: their impact on weather-related risk valuation will not be taken into account in this study.

Sunshine is also playing a significant role on crop quality, as it is one of the main factors of photosynthesis. The longer the sunshine during the vegetative period of grapevine, the more sugared and the less acid grapes will be. From this point of view, grapevine demands relatively luminous weather. Risk for crop quality is to receive insufficient sunshine, especially during maturation period. As sunshine is correlated with temperature, and its importance is less crucial than temperature under our latitudes, it won't be considered as a specific weather-related risk factor in this study.

Pluviometry has also its importance in grape quality: sugar-acidity-polyphenols relation is under dependence of considered terroir hydric regime. Best equilibrium is reached when grapevine is subjected to a rather humid weather (without any excess) till veraison (beginning in general at the end of July), to allow an optimal growth of the grapevine, and to a rather dry regime (without any excess) during maturation stage, to allow an optimal sugar accumulation in the berries, till the harvest generally conducted in September or October. In France, this factor presents a less important impact than temperature on grape quality; it mostly impacts yield.

I.2. <u>Weather-related risk and yield</u>

As for crop quality, weather conditions have a strong impact on yield. In this study, regulatory limits (defined for instance for French AOC, that have to comply with INAO decision), or voluntary limitations of yield will not be taken into account, as the goal of this study is exclusively weather-related risk.

Temperature has a direct effect on grapevine development and on yield. During winter, grapevine can cope with very low temperatures. From the end of flowering stage to the maturation period, temperature must reach a sufficient level (between 18°C to 25°C (64,40°F to 77,00°F)). Two main risks than can affect yield can be identified: frost and very high temperatures during a long period. Very strong frosts (below 5,00°F) can lead to partial or total destruction of stocks and roots; spring frosts can cause important damages after bud break. This risk will not be taken into account for two reasons: it can be limited by the use of agricultural processes[1] and can be insured. Finally, very high temperatures during an extended period can also

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[1] In areas particularly subject to frost, viticulturists have adapted grapevine work through specific techniques (artificial smoke clouds limiting temperature fall, late pruning…).

generate a lesser yield by leading to a "roasting" phenomenon and the drying out of the future crop.

Pluviometry also impacts yield. Rainfall levels from 400 to 600 millimeters per year represent ideal conditions for grapevine development. During winter, rains have no direct influence on the vineyard but allow the accumulation of water stocks that will be useful during spring and summer. At spring, rains are of great importance as grapevine growth depends on them. During summer, too high rainfall levels can lead to mildew development and threaten the crop. On the other hand, if hydric stock is insufficient, summer drought is also harmful to yield. These two risks are largely correlated with temperature risks mentioned further up (a rainy summer is generally cool, and a major drought is often accompanied by high temperatures). Researches in this paper are therefore limited to temperature risk study.

Fall rains happening before harvest may generate a development of grey mold and berry bursting. They can also hinder the harvest. Risks related to spring and fall rains are not being tackled in this paper. They may represent a valuable research path.

Finally, hail risk can destroy in a few minutes a whole crop. As it can be insured, this risk will not be taken into account.

I.3. Main risks to be covered by weather derivatives

Two kinds of climatic risks could therefore be covered by weather derivatives: insufficient mean temperatures from the end of the flowering stage to the harvest and too high temperatures during maturation stage.

II. FORESEEABLE WEATHER DERIVATIVES OFFER IN THE MEDIUM TERM

Weather derivatives are rather illiquid products, today available on the Chicago Mercantile Exchange, and dealt as OTC products in France. Energy companies dominate this market. Two factors explain this domination:

- *A volume effect*: weather-related risk is massive due to heating and cooling energy sales (dozens of Euros billions in France in 2003[2]), that are extremely correlated to temperature.
- *Their balanced cover needs*, favoring market liquidity: two energy companies may seek an opposite position at the same time. Indeed, high summer

[2] Household domestic energetic consumption reached Euros 35 billions in 2003 (« l'énergie en France – Repères » observatoire de l'énergie – MINEFI – édition 2004), and this consumption is for the most part linked to heating. Industrial and service energy consumption for heating purpose should also be added.

temperatures represent a risk for a company short in energy: these temperatures raise demand (higher air-conditioner consumption) and reduce some power plants capacities. On the other hand, they represent an opportunity for a "long" company (higher prices). Conversely, high winter temperatures represent an opportunity for a company short in energy and a risk for a "long" company: they reduce demand (lower heating related consumption) and therefore prices. A "short" energy company is to sell the weather derivative a "long" company is trying to buy.

Viticulturists, even if they decide to massively turn to weather derivatives, are to remain less important players in this market:

- Concerned volume is less important (11 Euros billions for the whole field in France)[3].
- All viticulturists have to cover the same kind of risk, which would result in a completely illiquid viticulture-specific market. Indeed, viticulturists are to look for covers against too low mean temperatures during vegetative period cover or overly high temperature, specifically before harvest… Some nuances may exist, depending on vineyards characteristics, but they are to be traduced by different strike prices rather than by bullish or bearish positions regarding the same product.

Therefore, the following hypothesis is retained: viticulturists could not benefit from a specific weather derivatives offer but will have to cover their needs having recourse to the weather derivatives commonly traded on the energy market. These weather derivatives have the following characteristics:

- *A mean daily temperature*, computed from data gathered in one or several meteorological stations. These means can be computed from minimal and maximal temperature on a 24 hours period, or from several temperatures measured at regular intervals during 24 hours (the latter better corresponding to energy companies needs).
- *Degree days*, computed as follows:
    - During summer : Max (mean daily temperature – 18°C (~65°F) ; 0)
    - During winter : - Min (mean daily temperature – 18°C (~65°F); 0)
- *A period* during which derivative is applied.
- *A strike*, given in number of degree days on the period.
- *A tick*, given in € per degree days, that allows the calculation of the pay-off.

[3] AFP dispatch – December 7th 2004

- *A pay-off*, computed as follows: cumulated number of degree days above or below strike during the concerned period multiplied by tick.
- *A premium*, fixed amount paid in advance by the derivative buyer.

III. STUDIED WEATHER DERIVATIVES

In the previous chapter, it has been set that the weather derivatives structure to be studied should be inferred from energy products. Weather derivatives parameters described above are therefore to be fixed to answer viticulturists needs.

III.1. Application period

In chapter 1, two major risks to be covered by viticulturists have been selected. These risks define an application period for related weather derivatives:

- *Too cold temperatures from the end of flowering stage to the end of the maturation*, corresponding to an application period from the 1st of July to the 30th of September.
- *Too high temperatures before the harvest*, corresponding to an application period from the 1st of August to the 15th of September[4].

These periods may be adapted to answer specific needs, such as vineyard at altitude, or to adapt these derivatives for areas outside France.

III.2. Choice and calculus of the underlying risk model

Application periods correspond to energy companies summer period. Underlying is therefore modeling using Cooling Degree Days, and is computed as:

$$\sum_{Application\ period} Max(mean\ daily\ temperature - 18°C;0) \qquad (18°C \sim 65°C)$$

Meteorological stations must be defined. Paris Montsouris and Bordeaux Mérignac have been chosen on the basis of following criteria:

- *Paris Montsouris* is the station the most likely to be chosen for the most liquid weather derivatives, therefore the most available for viticulturists. Indeed, liquidity is brought mainly by energy companies (cf. chapter II), and this station is representative of the most populated French area, and the one that use most energy. If the most liquid derivatives in France were to be based on a compound index made up from several different meteorological stations, weighting would be made notably from demographic criteria (corresponding to

[4] High temperatures favour an early harvest.

the number of final clients), or from weather sensitive energy consumption. In both cases, Parisian area is to have the strongest weighting.

- *Bordeaux Mérignac* is a station representative of a major wine producing area, with a climate significantly different from Parisian area.

III.3. Strike choice

Strike should have to be determined locally: depending whether the vineyard faces south, on wine production methods, on grape variety, each viticulturist will have to choose threshold beyond or over which yield or harvest quality is threatened. In fact, an expert will have to compute for each vineyard a threshold corresponding to a probability: for instance, the threshold corresponding to the coolest year in five years. Pricing study is therefore done choosing several strike levels.

III.4. Tick value

Tick value has no direct impact on the method of calculation of weather derivatives (the higher the tick, the more selective this kind of product is for small concerns).

IV. PRICING OF THE WEATHER DERIVATIVES STUDIED

Weather derivatives pricing has generated numerous papers. This pricing requires first to model temperature, then, from temperatures series, to model weather derivatives payoff, and finally, to infer corresponding premium.

IV.1. Temperature modeling

IV.1.1. Generic characteristics of temperature

From an intuitive comprehension of temperature, some characteristics are obvious:

- temperature is a seasonal phenomenon,
- temperature presents a several days correlation,
- temperature is stationary as a first approximation level.

These characteristics are the basis of all published temperature models, which can be brought together in two major types:

- mean-reversion models,
- autoregressive models.

IV.1.2. Two types of models presentation

IV.1.2.1. Mean-reversion models

Alaton, Djehiche and Stillberger (2001) propose this kind of model, based on an initial model from Dischel (2000).

The model is a mean-reversion model, defined by:

$$dT_t = \left(\frac{d\theta_t}{dt} + \alpha\left(\theta_t - T_t\right) \right) dt + \sigma_t dW_t \quad \text{with:}$$

$\theta_t = Trend_t + Seas_t$, the historical mean temperature for date t,

α, mean-reverting parameter,

σ_t, volatility,

W_t, a standard brownian movement.

Temperature at a date t is therefore given by:

$$T_t = \left(T_0 - \theta_0\right) e^{-\alpha t} + \theta_t + \int_0^t e^{-\alpha(t-u)} \sigma_u dW_u$$

Barrieu (2002) has shown this model is not fully adapted to weather derivatives modeling:

- Model is extremely sensible to □parameter calculation. This heavily limits its reliability.
- Temperature time-series simulation through this kind of modeling produces results far from other considered modeling and above all far from historical trend.

IV.1.2.2. Autoregressive models

These models are defined by:

$T_t = Trend_t + Seas_t + Corr_t + R_t$ with:

$Trend_t$, trend part of temperature, modeled as an time affine function with jumps, estimated on several years,

$Seas_t$, seasonal part of temperature,

$Corr_t$, an AR(n) type process modeling correlation,

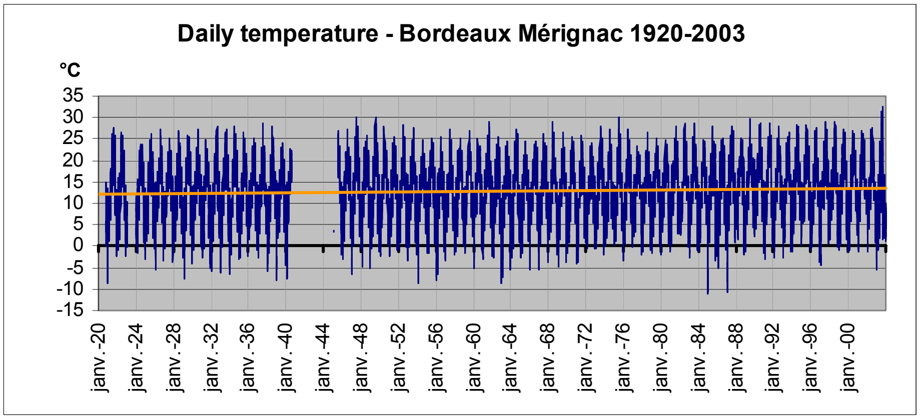
R_t, model residual.

These models produce better results than mean-reverting ones. They are further studied in this article.

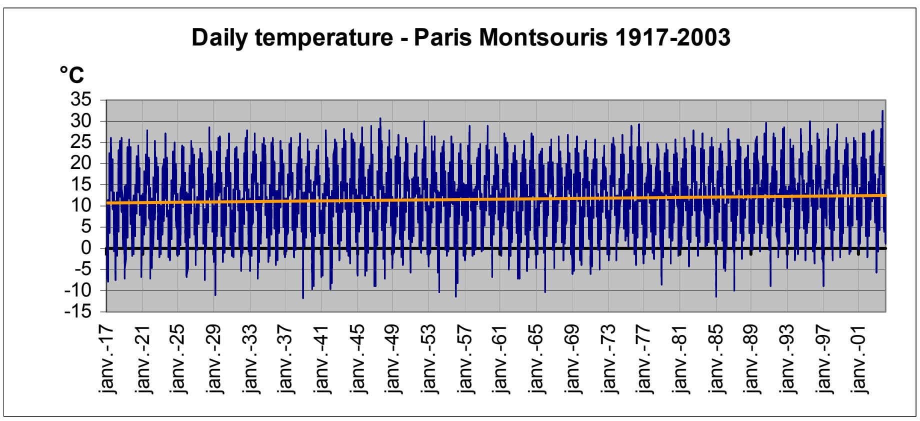
IV.1.3. Temperature modeling

IV.1.3.1. Determinist part estimation

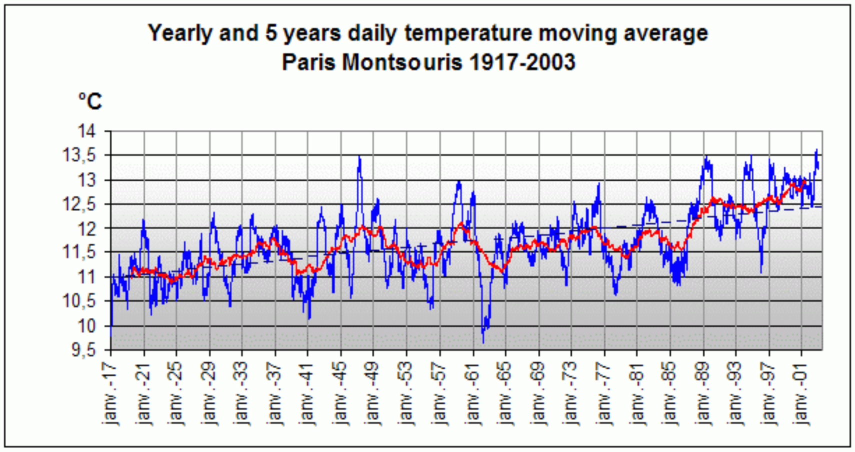
A first study of series over 80 years (partially incomplete for Bordeaux Mérignac) highlights the nearly stationary characteristics of the series.

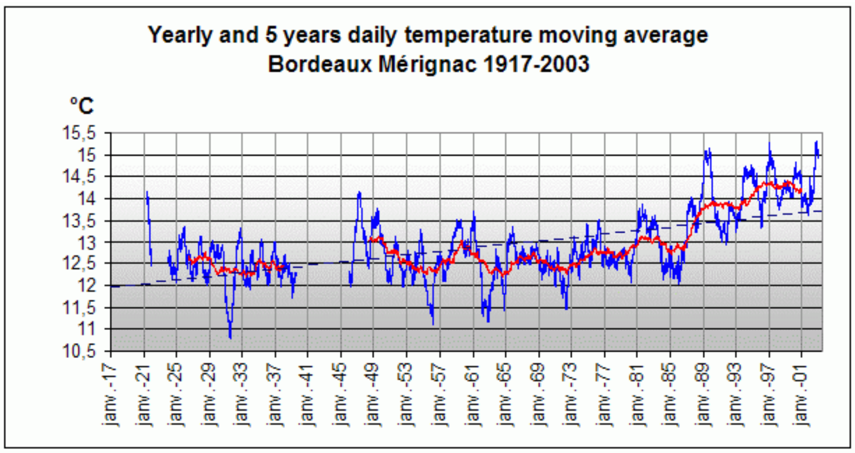


Though, five years moving average study shows a slight increase in mean yearly temperature.



- ***Trend growth modeling***





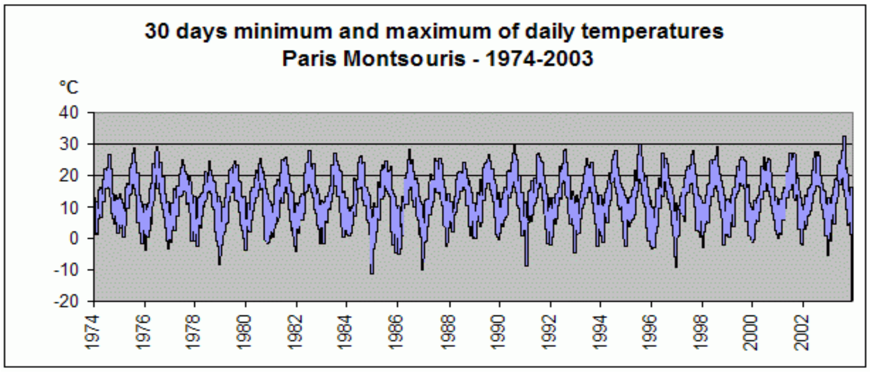
An acceleration of this growth seems to occur in 1985-1988. Barrieu (2002) observes the same trend rupture in 1985 for Paris Montsouris series. A first factor is to be taken into account: a rise of mean yearly temperatures. As suggested in other published papers (Barrieu, 2002) the modeling of this rise is defined by an affine function with a jump:

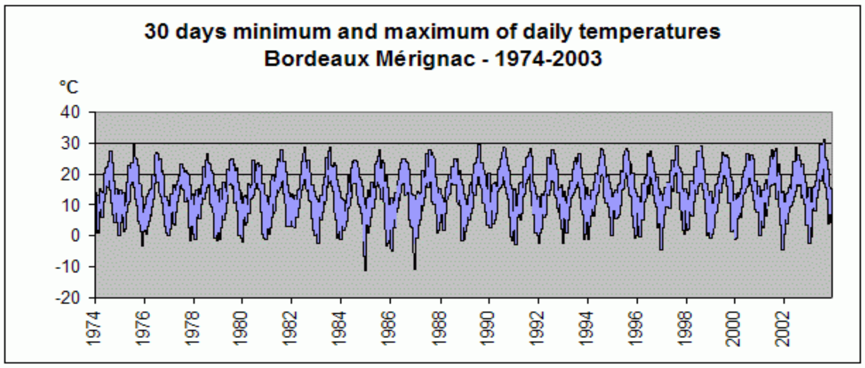
$$Trend_t = \begin{cases} \alpha_1 t + \beta_1 & \forall t < t_{breakpoint} \\ \alpha_2 t + \beta_2 & \forall t \geq t_{breakpoint} \end{cases}$$

Breakpoint and $\square_1$ and $\square_2$ parameters will be computed globally with all other determinist parameters (cf. infra).

<u>- Seasonality modeling</u>

Another factor to be taken into account in determinist modeling is seasonality. Seasonality can be clearly seen on 30 days minimum and maximum of daily temperatures.





To estimate this seasonality, "February 29th" are removed from the series to show yearly periodicity (Barrieu 2002; Diebold 2004).

Periodogram is computed using the following:

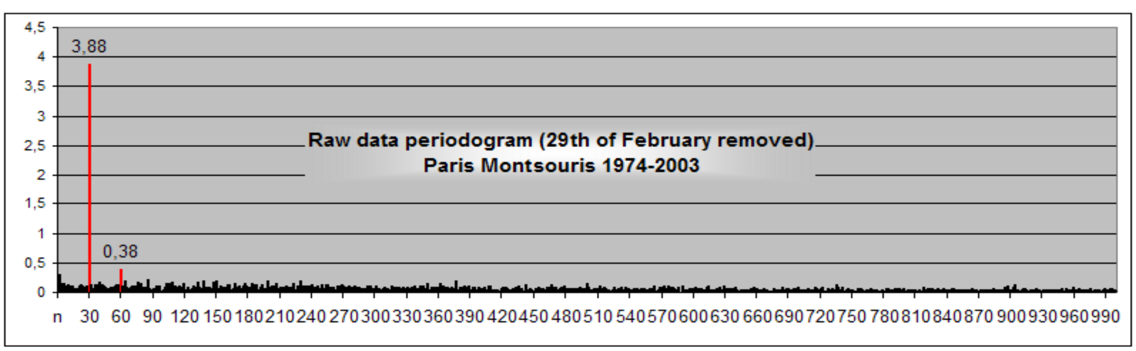
$$Periodogram(n) = \left| \sum_{k=0}^{N} T_k e^{i\frac{2k\pi n}{N}} \right| = \sqrt{\left(\sum_{k=0}^{N} T_k \cos\left(\frac{2k\pi n}{N}\right) \right)^2 + \left(\sum_{k=0}^{N} T_k \sin\left(\frac{2k\pi n}{N}\right) \right)^2} \text{ with :}$$

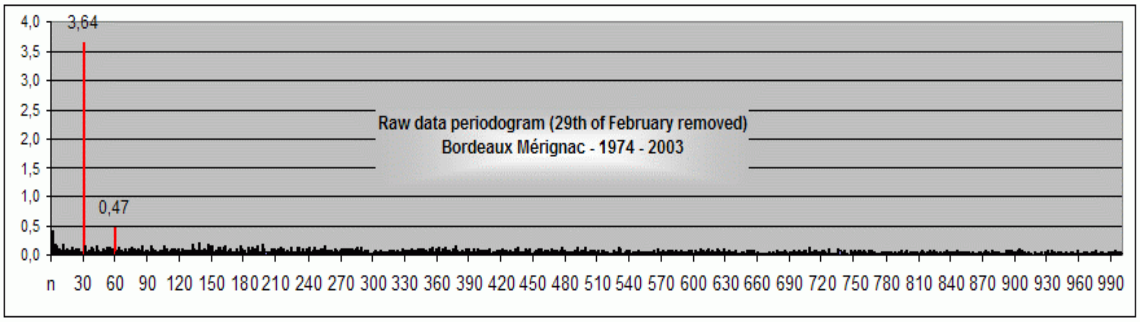
n, tested temperature function periodicity,

N, Sample size of data series (in this case 10950, corresponding to 30 years of daily data),

T_k, k^{th} sample temperature.

Following results are obtained:





Two spikes are clearly observed for n=30 (3,88 for Paris Montsouris, 3,64 for Bordeaux Mérignac), corresponding to a yearly frequency, and for n = 60 (0,38 for Paris Montsouris, 0,47 for Bordeaux Mérignac) corresponding to a half-yearly frequency. Every other periodogram values are inferior or equal to 0,2.

Seasonal component is therefore modeled with a sum of yearly and half yearly sinusoids:

$\boxed{Seas_t = a_1 \cos(2□t/365) + b_1 \sin(2□t/365) + a_2 \cos(4□t/365) + b_2 \sin(4□t/365)}$

<u>- Trend and seasonal parameters estimation:</u>

Following trend and seasonality parameters are computed: $□_1$, $□_1$, $□_2$, $□_2$, $t_{breakpoint}$, a_1, b_1, a_2, b_2. Proposed method to estimate these parameters is the following one:

- The series is first corrected from seasonal effects (computing of seasonal parameters a_1, b_1, a_2, b_2);
- Trend parameters $□_1$, $□_1$, $□_2$, $□_2$, $t_{breakpoint}$ are estimated from the series corrected from seasonal effects;
- Seasonal parameters a_1, b_1, a_2, b_2 are re-estimated once seasonal effects removed.

This iterative methodology is designed to correct potential bias caused by border effects, that cannot be completely neglected as the period studied is only a few decades.

<u>1st stage : initial correction of seasonal effect</u>

Following expression is minimized function of a_1, b_1, a_2, b_2, using a Newton algorithm:

$$|T_t - Seas_t| = \sqrt{\sum_{t=0}^{N}\left(T_t - \left(a_1\cos\left(\frac{2\pi t}{365}\right) + b_1\sin\left(\frac{2\pi t}{365}\right) + a_2\cos\left(\frac{4\pi t}{365}\right) + b_2\cos\left(\frac{4\pi t}{365}\right)\right)\right)^2}$$

Following values are obtained:

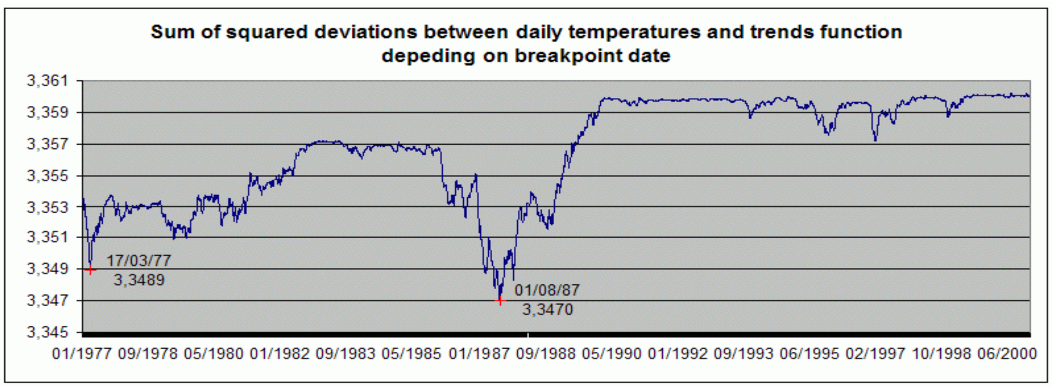
	Paris Montsouris	Bordeaux Mérignac
a_1	-7,347	-6,780
b_1	-2,470	-2,648
a_2	-0,021	-0,121
b_2	0,759	0,932

2nd stage : Trend calculation

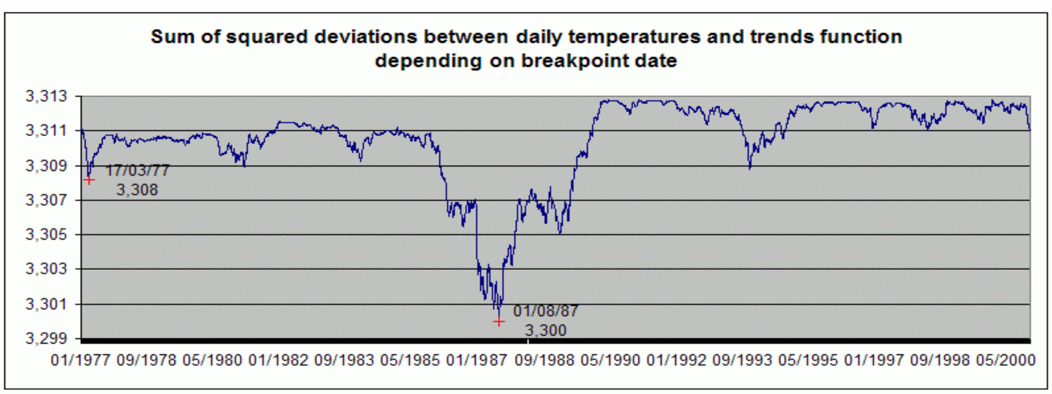
An empirical criterion is proposed to identify the breakpoint optimizing trend and time series adequacy. This criterion consists in minimizing the following function of $\square_1$, $\square_1$, $\square_2$, $\square_2$ using a Newton algorithm for every $t_{breakpoint} \in$ [1977/01/01; 2000/12/31]:

$$\left|T_t - Seas_t - Trend_t\right| = \sqrt{\sum_{t=0}^{t_{breakpoint}} \left(T_t - Seas_t - \alpha_1 t - \beta_1\right)^2 + \sum_{t=t_{breakpoint}+1}^{N} \left(T_t - Seas_t - \alpha_2 t - \beta_2\right)^2}$$

For Paris:



For Bordeaux:



Minimum is reached for Paris and for Bordeaux on the 1st of August 1987.

Choice of the breakpoint has a limited impact on adequacy between trend and observed temperature: deviation remains important (about 3°C ~ 38°F), and varies very slightly whatever the breakpoint chosen. This deviation remains too important to allow Chow test, for instance, to be conclusive on the validity of the breakpoint identified above.

The choice of this breakpoint has on the other hand a strong incidence on the resulting trend: if for instance trend had been estimated on the last ten years series, it would have been null, thus creating a deviation of 0,2°C (~ 32°F) in 2003.

Obtained results are the following:

	Paris Montsouris	Bordeaux Mérignac
Trend 01/1974 – 07/1987	-0,047°C/an	-0,011°C/year
Trend 08/1987 – 12/2003	+0,027°C/an	+0,040°C/year
Jump of the trend on August 1st 1987	+1,071°C	+1,094°C

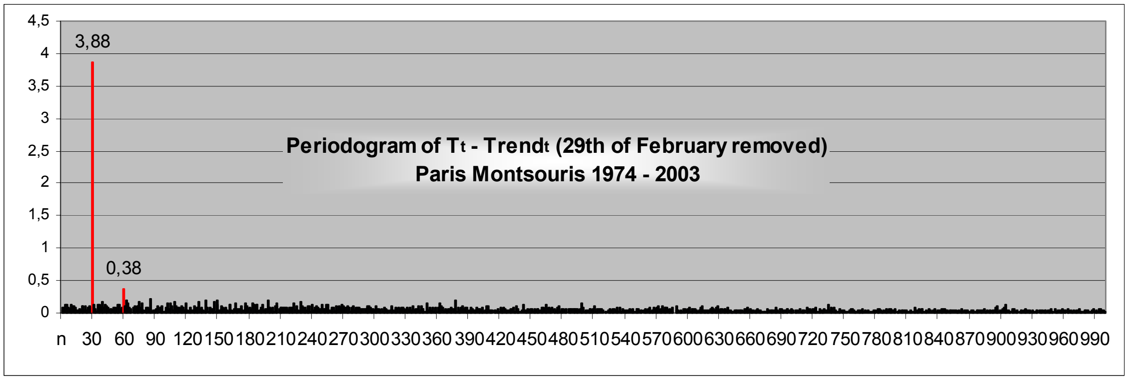
These results highlight 1987 jump importance.

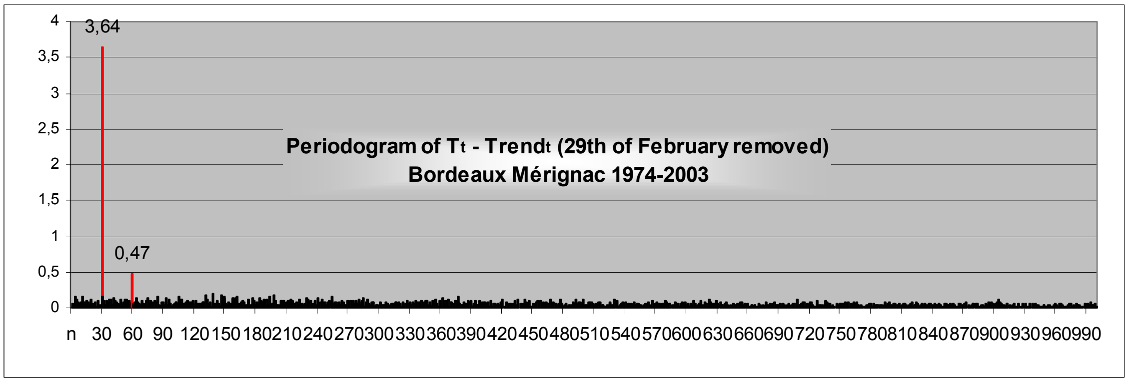
They also highlight linear modeling limits: slightly negative values observed on 74-87 period are negative, contrary to what could be observed on longer periods. Additional inquiry may be to use the results of physical modeling of the climate to precise this econometric approach oh the trend.

<u>3rd stage : 2nd iteration of seasonal effects correction</u>

a_1, b_1, a_2, b_2 parameters are computed from T_t - $Trend_t$, rather than from raw temperatures, to gain more precision in the estimation.

T_t - $Trend_t$ periodograms on the whole 1974-2003 period are more obvious than before: yearly and half-yearly spikes are better standing out.





Following results are obtained :

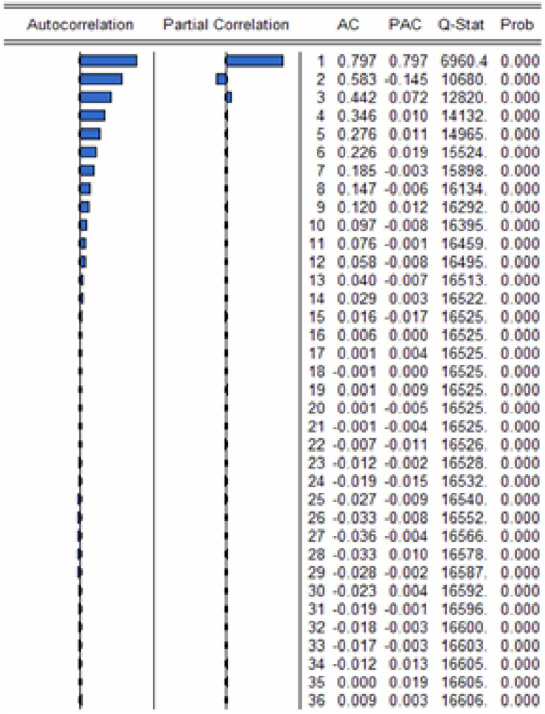
	Paris Montsouris		Bordeaux Mérignac	
	After iteration	Before iteration	After itération	Before iteration
a_1	-7,352 (-0,08%)	-7,347	-6,785 (-0,08%)	-6,780
b_1	-2,451 (+0,79%)	-2,470	-2,620 (+1,04%)	-2,648
a_2	-0,016 (+30,5%)	-0,021	-0,116 (+4,42%)	-0,121
b_2	0,761 (+0,25%)	0,759	0,937 (+0,60%)	0,932

IV.1.3.2. *Stochastic part estimation*

To model stochastic part, data autocorrelogram should be studied first.

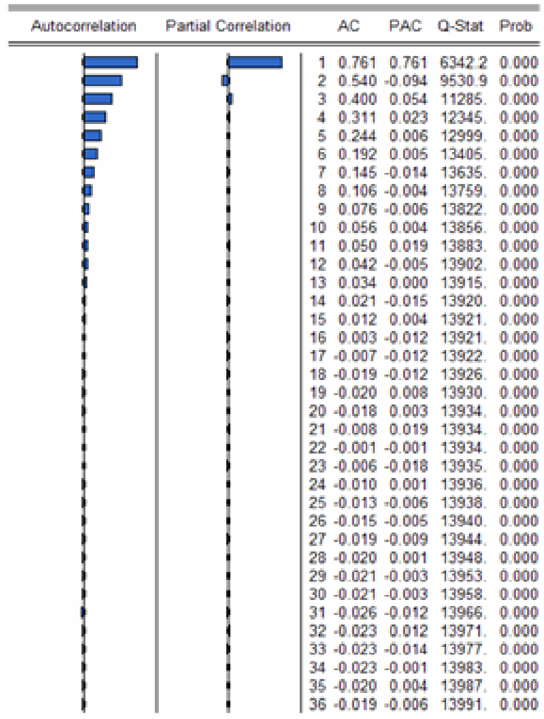
- *Data autocorrelogram*

Paris



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.797	0.797	6960.4	0.000
		2	0.583	-0.145	10680.	0.000
		3	0.442	0.072	12820.	0.000
		4	0.346	0.010	14132.	0.000
		5	0.276	0.011	14965.	0.000
		6	0.226	0.019	15524.	0.000
		7	0.185	-0.003	15898.	0.000
		8	0.147	-0.006	16134.	0.000
		9	0.120	0.012	16292.	0.000
		10	0.097	-0.008	16395.	0.000
		11	0.076	-0.001	16459.	0.000
		12	0.058	-0.008	16495.	0.000
		13	0.040	-0.007	16513.	0.000
		14	0.029	0.003	16522.	0.000
		15	0.016	-0.017	16525.	0.000
		16	0.006	0.000	16525.	0.000
		17	0.001	0.004	16525.	0.000
		18	-0.001	0.000	16525.	0.000
		19	0.001	0.009	16525.	0.000
		20	0.001	-0.005	16525.	0.000
		21	-0.001	-0.004	16525.	0.000
		22	-0.007	-0.011	16526.	0.000
		23	-0.012	-0.002	16528.	0.000
		24	-0.019	-0.015	16532.	0.000
		25	-0.027	-0.009	16540.	0.000
		26	-0.033	-0.008	16552.	0.000
		27	-0.036	-0.004	16566.	0.000
		28	-0.033	0.010	16578.	0.000
		29	-0.028	-0.002	16587.	0.000
		30	-0.023	0.004	16592.	0.000
		31	-0.019	-0.001	16596.	0.000
		32	-0.018	-0.003	16600.	0.000
		33	-0.017	-0.003	16603.	0.000
		34	-0.012	0.013	16605.	0.000
		35	0.000	0.019	16605.	0.000
		36	0.009	0.003	16606.	0.000

Bordeaux



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.761	0.761	6342.2	0.000
		2	0.540	-0.094	9530.9	0.000
		3	0.400	0.054	11285.	0.000
		4	0.311	0.023	12345.	0.000
		5	0.244	0.006	12999.	0.000
		6	0.192	0.005	13405.	0.000
		7	0.145	-0.014	13635.	0.000
		8	0.106	-0.004	13759.	0.000
		9	0.076	-0.006	13822.	0.000
		10	0.056	0.004	13856.	0.000
		11	0.050	0.019	13883.	0.000
		12	0.042	-0.005	13902.	0.000
		13	0.034	0.000	13915.	0.000
		14	0.021	-0.015	13920.	0.000
		15	0.012	0.004	13921.	0.000
		16	0.003	-0.012	13921.	0.000
		17	-0.007	-0.012	13922.	0.000
		18	-0.019	-0.012	13926.	0.000
		19	-0.020	0.008	13930.	0.000
		20	-0.018	0.003	13934.	0.000
		21	-0.008	0.019	13934.	0.000
		22	-0.001	-0.001	13934.	0.000
		23	-0.006	-0.018	13935.	0.000
		24	-0.010	0.001	13936.	0.000
		25	-0.013	-0.006	13938.	0.000
		26	-0.015	-0.005	13940.	0.000
		27	-0.019	-0.009	13944.	0.000
		28	-0.020	0.001	13948.	0.000
		29	-0.021	-0.003	13953.	0.000
		30	-0.021	-0.003	13958.	0.000
		31	-0.026	-0.012	13966.	0.000
		32	-0.023	0.012	13971.	0.000
		33	-0.023	-0.014	13977.	0.000
		34	-0.023	-0.001	13983.	0.000
		35	-0.020	0.004	13987.	0.000
		36	-0.019	-0.006	13991.	0.000

Autocorrelograms show significant partial autocorrelations at the order 3 (every partial autocorrelation at a superior order are inferior or equal to significativity threshold, equal to $2/\sqrt{Sample\ size} = 0{,}019$). The AR3 model that has been developed in numerous papers (Cao & Wei, 2000; Tankov 2001; Roustant 2001; Barrieu 2002) is therefore retained. Its parameters are named ϕ_1, ϕ_2, ϕ_3.

- *Residual Rt modeling*

$\sqrt{\sum_{k=4}^{N} \left(R_t - \phi_1 R_{t-1} - \phi_2 R_{t-2} - \phi_3 R_{t-3}\right)^2}$ minimum is computed (ordinary least squares fitting method) to estimate ϕ_1, ϕ_2, ϕ_3.

Following results have been obtained:

	Paris Montsouris	Bordeaux Mérignac
ϕ_1	0,923	0,838

$\square_2$	-0,210	-0,139
$\square_3$	0,072	0,054

- <u>*$\square_t$ residual of the AR(3)*</u>

Diebold (2004) has suggested that residual seasonality is most often seasonal. To identify the seasonal component, residuals are modeled as follows:

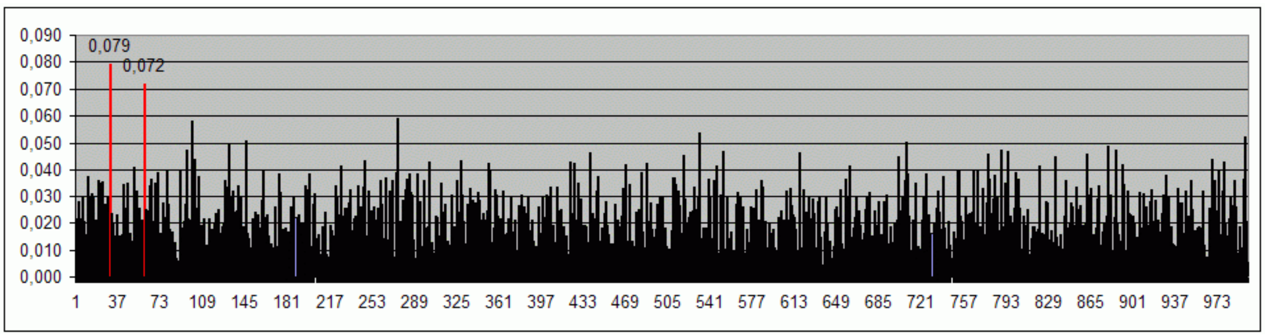
$\square_t = \square_t\square_t$ where σ_t is AR residual volatility, supposed strictly positive, non constant in time.

Squaring this expression, then raising it to logarithm, the following result is obtained:

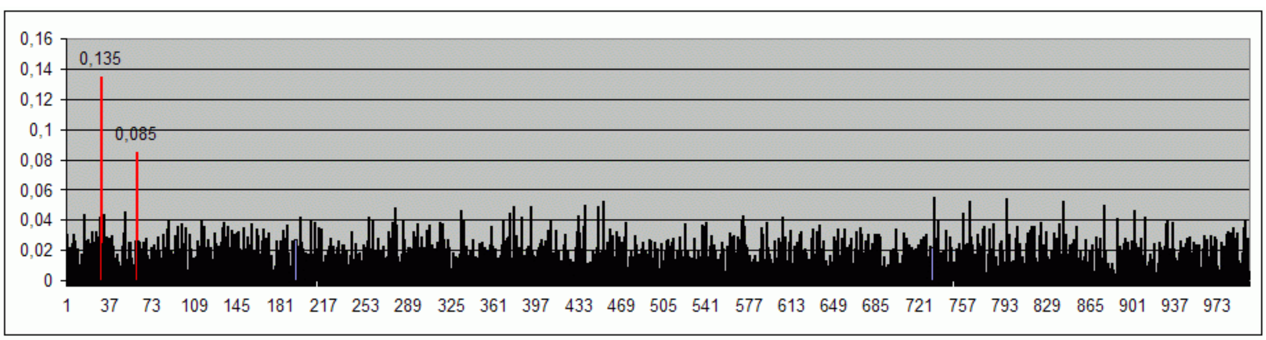
$\ln(\square_t^2)=2.\ln(\square_t)+\ln(\square_t^2)$

$\ln(\square_t^2)$ is supposed not seasonal. $\ln(\square_t^2)$ periodogram is therefore computed.

For Paris Montsouris:



For Bordeaux Mérignac :



A yearly and half-yearly periodicity for $\square_t$ can be inferred.

$\square_t$ is modeled by $\square_0$ + a $\cos(2\square t/365)$+ b $\sin(2\square t/365)$+ c $\cos(4\square t/365)$+ d $\sin(4\square t/365)$.

Modeling parameters are estimated minimizing $\square\ln(\square_t^2)^2$ which is likelihood logarithm.

Following results are obtained:

	Paris Montsouris	Bordeaux Mérignac
$\square_0$	1,058	1,117
a	0,031	0,152
b	0,075	0,019
c	0,066	0,084
d	-0,037	-0,047

AR3 parameters are then computed again to minimize $\square_t$

	Paris Montsouris		Bordeaux Mérignac	
	After iteration	Before iteration	After itération	Before itération
$\square_1$	0,919 (-0,4%)	0,923	0,838 (+0,03%)	0,838
$\square_2$	-0,208 (+1,0%)	-0,210	-0,145 (-4,3%)	-0,139
$\square_3$	0,072 (+0,3%)	0,072	0,057 (+4,7%)	0,054

The resulting noise presents satisfactory characteristics:

- it doesn't present significant autocorrelation,
- it doesn't present significant seasonality,
- it seems stationary,
- its 3rd and 4th order moments are close from being Gaussian, even though Jarque Bera test doesn't conclude this kind of modeling should be considered.

This noise will therefore be generated numerically, using its inverse repartition function.

IV.1.3.3. Temperature modeling conclusion

Temperature has been modeled on 1988-2003 period as presented below:

$T_t = Trend_t + Seas_t + R_t$ with

$Trend_t = □_2 + □_2 t$

$Seas_t = a_1 \cos(2□t/365) + b_1 \sin(2□t /365) + a_2 \cos(4□t /365) + b_2 \sin(4□t /365)$

$R_t = □_1 R_{t-1} + □_2 R_{t-2} + □_3 R_{t-3} + □_t □_t$ with

$□_t □ □_0 + a \cos(2□t/365) + b \sin(2□t/365) + c \cos(4□t/365) + d \sin(4□t/365)$

$□_t$ a noise numerically generated from its inverse repartition function.

IV.2. Pay-off estimation of weather derivatives considered

Following notations are proposed: weather derivatives corresponding to 1er of July to 30 September will be called “long” products, and weather derivatives corresponding to 1er of August to 15 August will be called “short” products.

Corresponding premium P can be simply computed using following expression:

P = E[pay-off] + ̃□□[pay-off], with □ the seller risk aversion parameter.

A viticulturist that wishes to use weather derivatives would express his need as: « I wish a pay-off superior or equal to X for a risk level that occurs 20% or 30% of years (what he would consider as “bad seasons” from a climatic point of view), and to pay the smallest premium ».

Following notations are proposed (taking the case of a pay-off fixed for 30% of years):

- CDD Cooling Degree Days,
- U the “underlying” (corresponding to Cooling Degree Days sum on the period, in °C.days),
- $U_{30\%}$ the underlying level verifying $Prob(U<U_{30\%})=30\%$,
- U_{sup} the strike for the “long” product,
- t the tick,

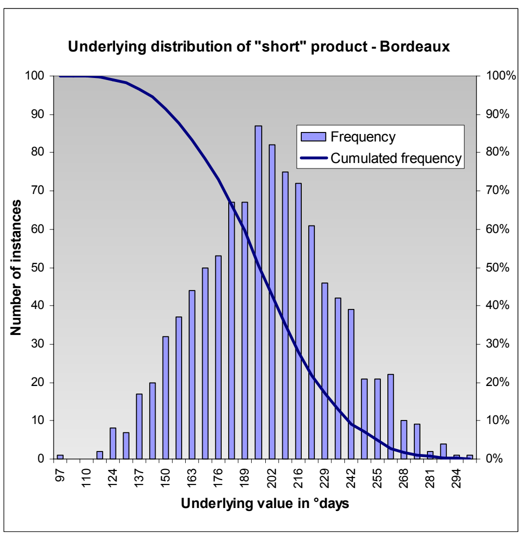
Viticulturist request (for the “long” product) corresponds to the search for U_{sup} minimizing premium under the constraint of a pay-off at $U_{30\%}$ equal to X, which means to search for U_{sup} minimizing (E[max(U_{sup}-U ; 0)]+̃□□[max(U_{sup}-U ;0)]).t under the constraint (U_{sup}-$U_{30\%}$).t = X.

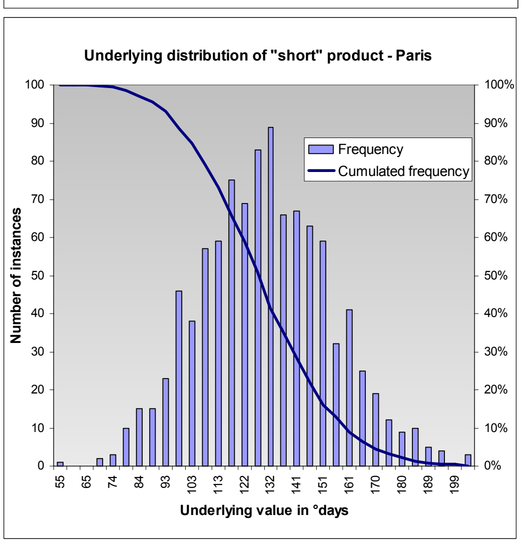
Answer viticulturist request would therefore consist in determining:

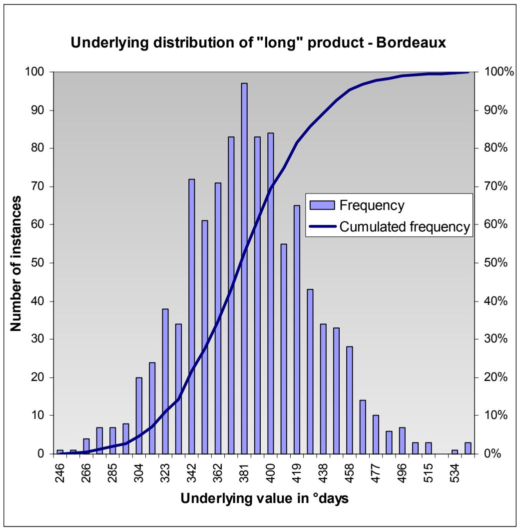
$$U_{sup} \text{ minimizing } \frac{E\lfloor \max(U_{sup} - U;0)\rfloor + \lambda.\sigma\lfloor \max(U_{sup} - U;0)\rfloor}{U_{sup} - U_{30\%}}$$

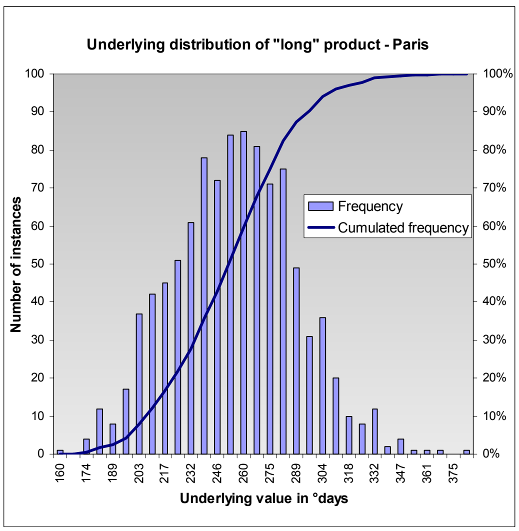
To determine U_{sup} of the product corresponding to viticulturist request, it is therefore necessary to identify $U_{30\%}$ with a sufficient precision.

To do so, 1000 yearly temperature series are computed for Paris and Bordeaux using the above temperature model. For each of these series, underlying U is computed. Underlying U distribution can be numerically estimated from these series, and is represented below for each of considered products. Weather derivatives pay-off described in chapter II can be inferred fixing strike and tick t. Corresponding premiums could also be computed fixing risk aversion parameter □.









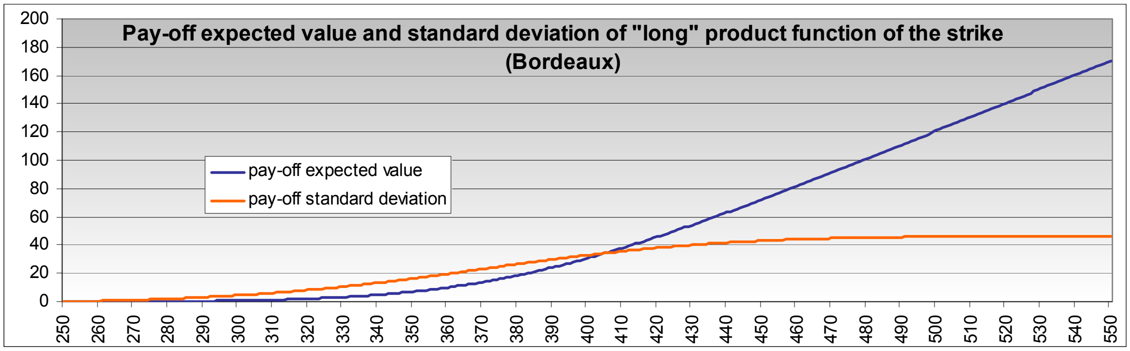
So, for Bordeaux "long" product, $U_{30\%}$ = 355°C/days and $U_{40\%}$ = 367°C/days. This highlights the accuracy need for temperature modeling to correctly price these products: between those two values, deviation is only 12°C/days for a 3 months period. Mean daily temperature bias must therefore be inferior to 0,375°C (~ 0,675°F) to offer a risk cover precise by ± 10 %.

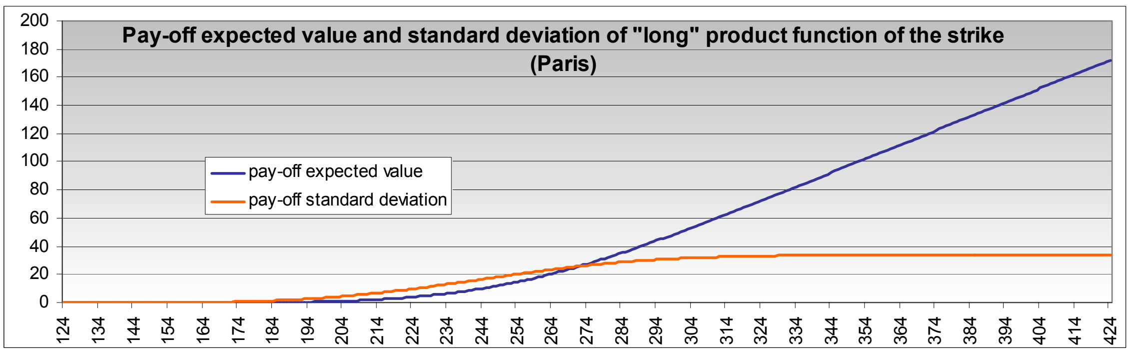
This is on the same scale as non stationarity identified in chapter IV.1.3.1. To price with a precision better than ± 10 %, it seems necessary to refine trend modeling.

These graphs highlight also significant differences between Paris and Bordeaux:

- The abscissas are shifted, which reflects the gap between those two cities gap.
- Underlying distribution of the "long" product is strongly asymmetrical, due to the 18°C threshold, reached much more often in Paris than in Bordeaux in July and in September.

Temperature series also allow the computing of expected value and standard deviation of the pay-off, function of the strike, and therefore, of the premium.





This highlights several major differences between Bordeaux and Paris:

- Curbs are shifted by the mean temperature gap between those two towns (graphs scales have also been shifted to simplify comparison);
- Standard deviation is higher for Bordeaux, which can rise the cost of these products, particularly if risk aversion parameters are high;
- Differences on "long" product due to higher impact of the threshold of 18°C on Paris CDD are found again: pay-off expected value is truncated for the first values of the strike.

Even before the study of the correlation between Paris and Bordeaux temperatures, these differences are important enough to conclude that two identical products, one based on Paris temperatures and the other on Bordeaux temperatures, would present a significant price gap.

V. Discussion and implication

Given the technical issues concerning the pricing of weather derivatives, it cannot be proposed as such to viticulturists. Two ways of implementation can be foreseen :

- To turn to brokers to market these products. Indeed, they can deliver some of the necessary communication and formation to viticulturists. On the other hand, they will generate additional transaction costs.
- These products can be used by insurance companies as an alternative solution to reinsurance. These products allow the transfer of some of the price and the volume risks to a more liquid energy market. They are therefore useful products for companies proposing crop and revenue insurance.

To validate this approach, a study should be lead with viticulturists to confirm the choice of the weather risks covered. Two comparaisons should also be lead :

- between the pay-off and viticulturists revenue,
- between the pay-off and crop and revenue insurance indemnisation.

A complete pricing, including management costs, should then be defined for specific areas. A first business model of the product could then be realised, and confronted to a panel of viticulturists and of insurance companies.

On the basis of a study on the weather-related risks viticulturists have to face, suitable products for the management of these risks have been proposed. Temperatures of Paris and Bordeaux have been carefully modeled so as to propose a method allowing the set up of a pricing. Compared to the latest published papers, gains of precision were sought by developing several elements. Determinist part has been refined proposing an empirical criterion to identify the trend breakpoint, and to estimate seasonal and trend parameters through two iterations. Stochastic parameters were estimated using generalized least squares fitting method, which has brought an increase of autoregressive model accuracy. Finally, instead of estimating residual noise using a Gaussian or hyperbolic distribution, a numerical estimation based on the inverse repartition function.

From this study, several research paths can be foreseen.

First, climate modelisation can be further improved. Concerning determinist modeling, climate physical modeling results may be used, particularly to define the trend. Besides, this paper is not tackling the issue of correlation between temperature risks measured at Bordeaux Merignac meteorological station, and risks actually concerning such or such vineyard in the area. To better estimate derivative products adaptation, this hypothesis could be studied comparing Bordeaux temperatures series, and temperatures series measured directly on vineyards. This kind of research can be lead using mini-meteorological station on field that allow experts to infer relationships between the two temperature series.

Another research path would be to correlate several cities temperatures to confirm the necessity of designing local products.

The study of pluviometry-related risks, and their correlation with temperature risks, could be a major supplement to this paper.

Secondly, to better evaluate the attractivness of the product, correlation between climate and either viticulturists revenues or insurance indemnisation can be further modelised.

Finally, a behavioral study could complete the understanding of how viticulturists would use this kind of products.

REFERENCES

Alaton, P., Djehiche B., & Stillberger D. (2001). On modeling and pricing weather Derivatives. *Working Paper*.

Alleweldt, G., & Ruehl, E. (1982). Utersuchungen zum Gaswechsel der Rebe. I. Einfluss von Temperatur, Blattalter und Tageszeit auf Nettophotosynthese und Transpiration. *Vitis, 21*, 93-100.

Barrieu, P. (2002). Produits dérivés météorologiques et environnement. Thèse de Doctorat en Sciences de gestion. HEC Paris.

Campbell, S., & Diebold, F. (2004). Weather Forecasting for Weather Derivatives. *Working Paper*. Center for financial studies. Goethe-Universität-Frankfurt.

Christoffersen, P. & Diebold, F. (2004). Financial Asset Returns, Direction-of-Change Forecasting, and Volatility Dynamics. *Working paper*. Wharton School.

Cao, M. & Wei, J. (2000). Pricing the weather. Risk Magazine, 67-70.

Dischel, R. (1998). Black-Scholes won't do. Risk Magazine, E.P.R.M., October, 8-13.

Dischel, R. (1999). Shaping history. Risk Magazine, E.P.R.M., October, 13-15.

Dischel, R. (2000). Seasonal weather forecasts and derivative valuation. Risk Magazine, E.P.R.M., juillet, 18-20.

Documents from C.M.E website, http://www.C.M.E.com.

Documents from Artémis website, http://www.artemis.com.

Documents from the Weather Risk Management Association website, http://www.wrma.org.

Data from the European Climate Assessment and Dataset website, http://www.knmi.nl.

Happ, E. (1999). Indices for exploring the relationship between temperature, grape and wine flavour. *Wine Industry Journal 14(4)*, 1-5.

Kliewer, W.M. (1970). Effect of day temperature and light intensity on colouration of Vitis vinifera L. grapes. *Journal of American Society of Horticultural Science, 95,* 693-697.

Makki, S. (2002). Crop Insurance: Inherent Problems and Innovative Solutions. *Agricultural Policy for the 21st Century,* Luther Tweeten, Stanley R., Thompson. Ames. Iowa State Press.

Moreno, M. (2003). Evaluation des dérivés climatiques. *Working Paper*. Université Claude Bernard. Villeurbanne.

Observatoire de l'énergie, MINEFI. (2004). L'énergie en France – *Repères*.

Risk Magazine, 1998. Weather risk special report.

Risk Magazine, 1999. Weather risk special report.

Risk Magazine, 2000. Weather risk special report.

Risk Magazine, 2001. Weather risk special report.

Roustant, O. (2001). Une application de deux modèles économétriques de température à la gestion des risques climatiques. *Working Paper*.

Skees, Jerry R. (2001). The Bad Harvest . *Regulation,24,* 16-21.

Tankov, P. (2001). Modélisation des données de températures: cas univarié. *Working Paper.*