Climate and Finance

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Summary

The influence of global climate variability on the prices of nine different commodities as noted at the New York commodity exchange was investigated. The combination of pattern recognition methods and multivariate linear and nonlinear modeling yields statistically significant relations between global climate variability and commodity price volatility.

Large-scale sea surface temperatures in the Pacific and the Atlantic have significant impact on the prices of soybean, soybean oil, soybean meal, and to a lesser degree on wheat and corn. Up to 60% of the price variations of some commodities are a direct consequence of climate variations. The found relations are robust and are strong enough to yield extremely valuable information. They are useful to analyze and judge the price of a range of commodities. In combination with seasonal climate forecasting they may be exploited to yield price forecasts on lead times between three and six months.

1. The problem

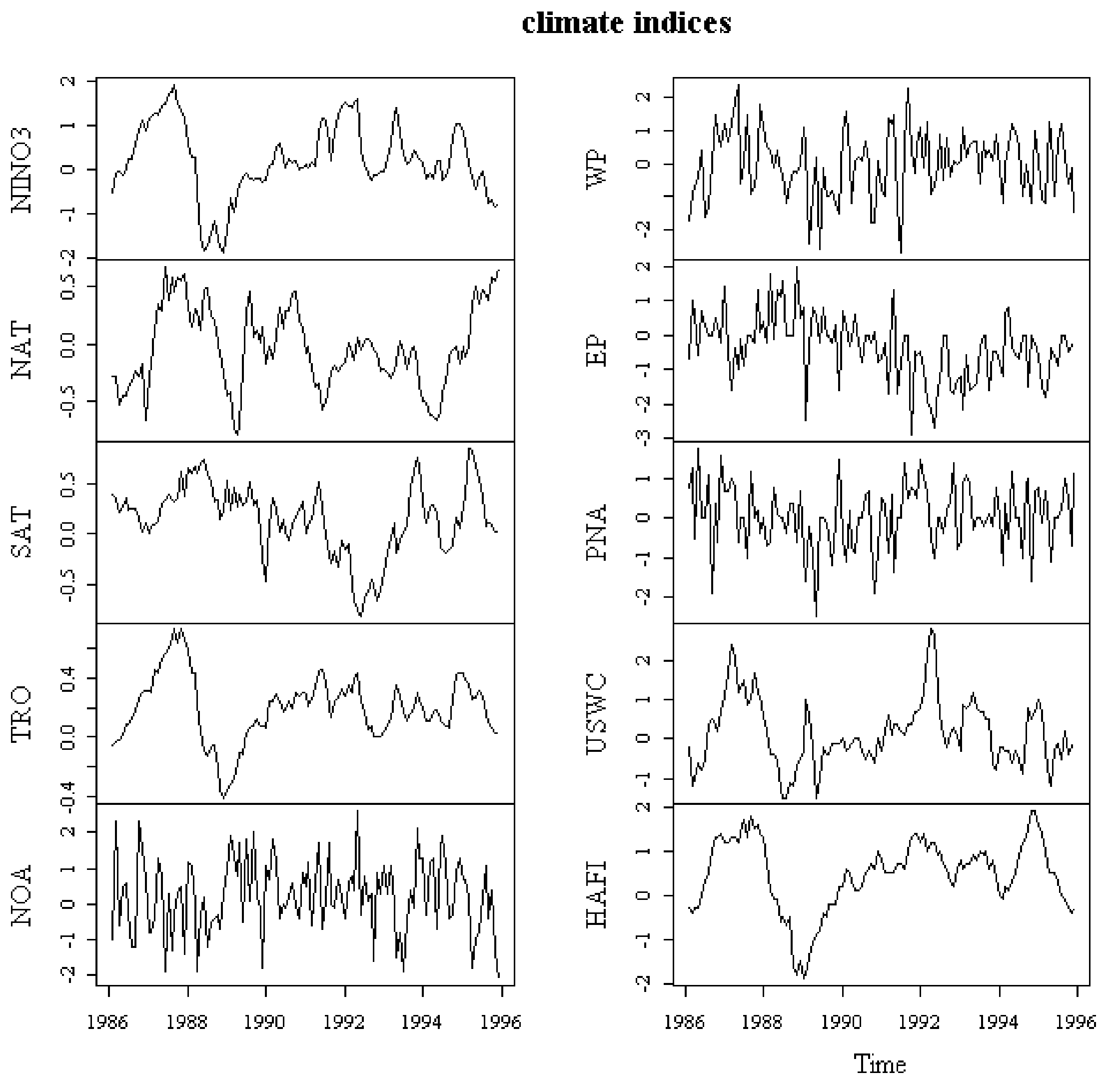
Large-scale climate phenomena may strongly influence economics worldwide. Recognizing and understanding relationships between climate and economics hence may provide a valuable source of information. The noisy character of both, climate and economics, however, makes it extremely difficult to identify dominant links, to understand the governing mechanisms, and to exploit them. Companies, operating in climate sensitive fields may encounter substantial difficulties during decision-making processes in areas like logistics, pricing, estimation of production costs, resource management, market analyses, and profit estimates.

Recently substantial progress in the development of powerful methods to detect signals and patterns in complex and noisy data sets has been achieved. Such algorithms in conjunction with the enormous progress in short range climate forecasts open up new avenues to improved business strategies.

It is reasonable to assume that large-scale climate variations may affect commodity prices. However, it is also clear that climate is not the only factor that influences these prices. It is therefore necessary to investigate which commodities are mostly affected by climate and which portion of the price volatility can be explained by climate variability. Knowing these numbers provides a more comprehensive picture of the actual market situation and thus enables better and more precise decisions.

2. Data

The climate data and commodity prices used in this study cover the period February 1986 to December 1995. To monitor the world climate ten commonly used climate indices were analyzed.

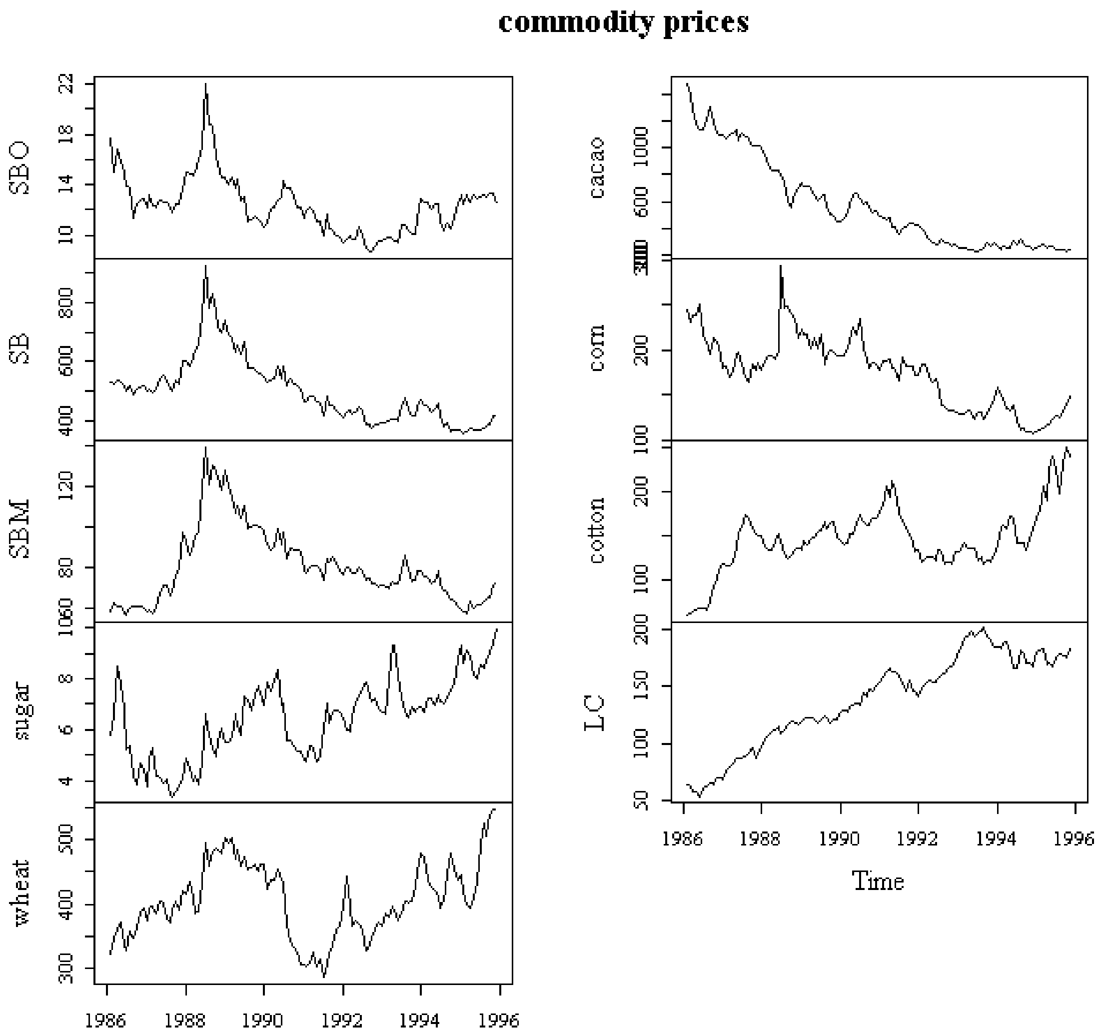


The climate indices are related to the prices of nine commodities as traded at the New York commodity exchange. The abbreviations in brackets are used in this paper to label the plots.

1. Soy bean oil (SBO)
2. Soy bean (SB)
3. Soy bean meal (SBM)
4. Sugar
5. Wheat
6. Cacao
7. Corn

8. Cotton
9. Live Cattle (LC)

The time series of the prices are shown in the following figure.



3. Methodology

The objective is to find statistically significant and robust relationships between climate indices and commodity prices. A mathematical model, relating climate and prices to each other has to be found. The difficulty, however, is that the data are noisy. It must be ensured that the model does not over-fit the data. Furthermore, it has to be investigated which climate indices are most useful for that purpose and which commodity prices can be predicted or reconstructed from climate indices.

The first step is to separate the problem into predictable signals and unpredictable noise. The decision of what to call “signal” and what to call “noise” is non-trivial. A powerful method to do so is the expansion of the problem into a few characteristic “guess patterns”. In many cases only a few of such patterns are sufficient to explain the major part of the behavior of the system (climate and prices). The specification of those characteristic patterns can be done in various ways depending on the problem. Once significant patterns are found they form the basis to identify statistical relationships between climate indices and commodity prices.

Based on this, the algorithm to find robust relationships between climate and prices is as follows:

1. Identify the dominant patterns for the climate indices and the commodity prices and store them
2. Project the original data onto the respective patterns to obtain the time evolution coefficients of the patterns.
3. Determine a statistical model that describes the relationship between the dominant climate patterns and the dominant price patterns. Use this model to transform price patterns into climate patterns
4. Use the obtained price patterns to reconstruct and predict actual commodity prices.

Signal and noise are separated from each other in an objective and natural way. In contrast to classical filtering methods this approach does not need any ad hoc assumptions. Various pattern recognition methods and statistical modeling algorithms were combined, yielding 4 different forecast systems with comparable skills.

4. Results

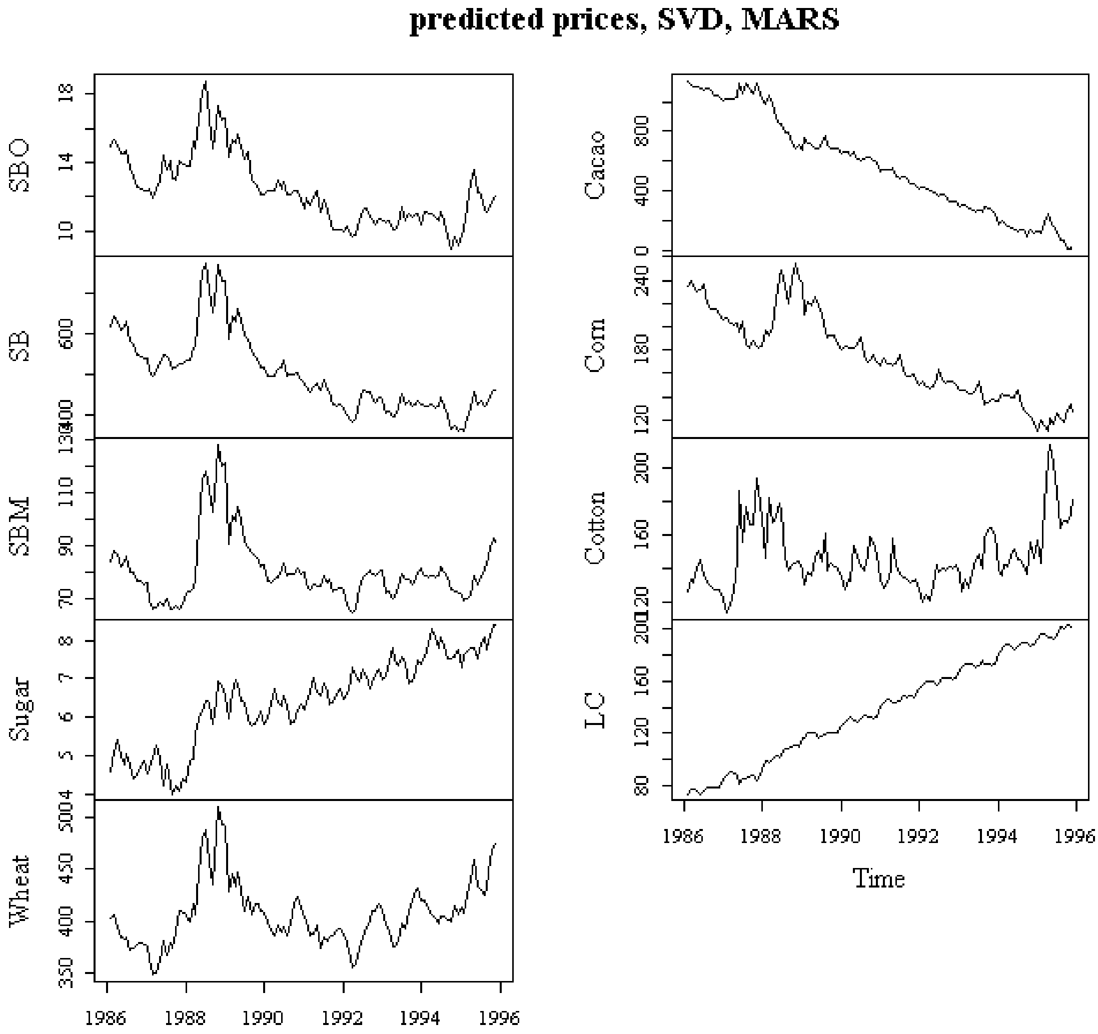
Some results obtained with the analysis systems are presented in this section. In Fig.3 we present reconstructed commodity prices based on a combination of singular value decomposition (SVD) and multivariate adaptive regression splines (MARS). Similar results were obtained with the other three methods. Quantitative skill measures for all four methods are given in the tables below. The explained variance and the correlation between reconstructed and actual prices were computed for that purpose.

Table 1	**SBO**	**SB**	**SBM**	**Sugar**	**Wheat**	**Cacao**	**Corn**	**Cotton**	**LC**
Exp.var	49 %	48 %	33 %	10 %	22 %	14 %	31 %	22 %	2 %
Corr	0.71	0.69	0.57	0.32	0.48	0.38	0.56	0.47	0.16

Table 2	**SBO**	**SB**	**SBM**	**Sugar**	**Wheat**	**Cacao**	**Corn**	**Cotton**	**LC**
Exp.var	52 %	65 %	51 %	17 %	36 %	22 %	29 %	21 %	16 %
Corr	0.72	0.81	0.71	0.42	0.60	0.47	0.54	0.47	0.40

Table 3	SBO	SB	SBM	Sugar	Wheat	Cacao	Corn	Cotton	LC
Exp.var	52 %	50 %	35 %	11 %	26 %	18 %	34 %	24 %	3 %
Corr	0.72	0.71	0.6	0.33	0.51	0.42	0.58	0.49	0.17

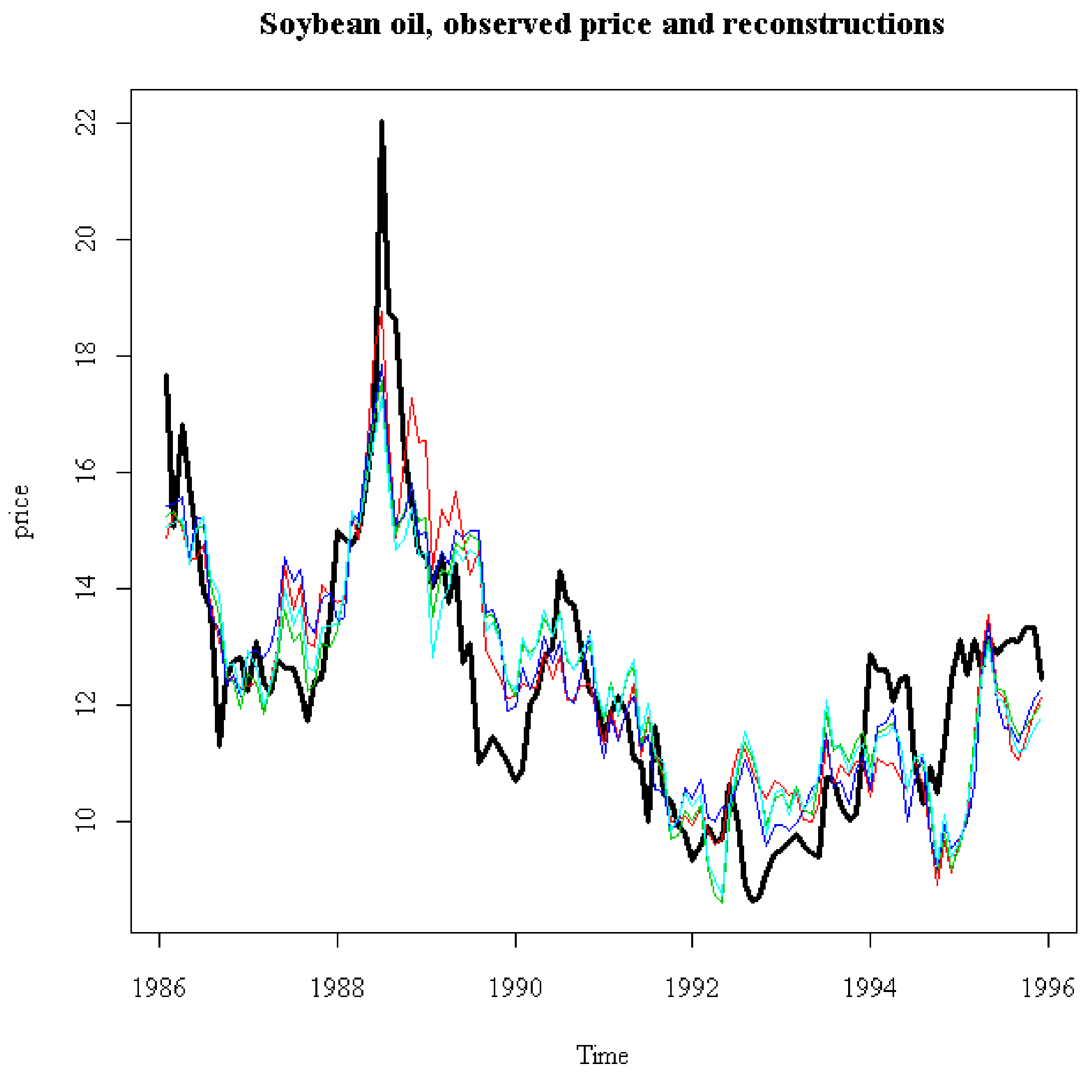
Table 4	SBO	SB	SBM	Sugar	Wheat	Cacao	Corn	Cotton	LC
Exp.var	51 %	64 %	50 %	5 %	31 %	23 %	36 %	21 %	7 %
Corr	0.71	0.80	0.71	0.26	0.56	0.48	0.60	0.46	0.28



In the next figure we present the four individual reconstructions of soybean oil prices and compare it with the actual prices (thick solid line). The overall agreement is rather good and seems to be sufficient to be financially exploited. It is worth emphasizing that the residual between the reconstructions and the actual prices has a red noise spectrum. The understanding of the relationship between climate and soybean oil prices thus enables traders to watch for outliers, i.e. significant differences between climate-reconstructed prices and the actual prices and to act accordingly.

The analyses can be summarized as follows:

1. Statistically significant relations between climate variability and the price of some commodities could be identified. The main predictors are sea surface temperature variations in the Pacific and the Atlantic.
2. These variations can explain up to 60% of the total price variability, depending on the commodity. This portion is big enough to base business strategies upon it.
3. The residual signal (the part not explained by climate) is at least for some commodities red noise, which implies that there is no other predictable mechanism influencing the prices of those commodities.



5. Forecasts

So far we only spoke about analyses but not about forecasts. The statistical relations found in the previous sections can be used to perform actual price forecasting. As predictors we used large-scale sea surface temperature variations in the Pacific and the Atlantic. Nowadays such variations can be predicted with high accuracy on lead times up to 6 months, under certain conditions even up to one year. International climate prediction centers start carrying out such predictions on a routinely basis. In the US, Europe, Japan, and Australia forecast systems, based on numerical climate models have reached a state of maturity that enables them to go operational in the very next future. On lead times up to about 3 months the success of these systems, expressed as anomaly correlations between observations and predictions is of the order 0.8 and better.

With our statistical models we may transform those climate forecasts directly into price forecasts.

6. What next ?

The same analysis should be repeated with longer, more recent time series. The limiting factors of this study were the commodity prices. Climate indices are accessible up to present (one month delay). Furthermore, other commodities should be included. Coffee, tea, rice, palm oil, and probably some fruits are candidates to be looked at. Especially coffee is interesting since it is an extremely important commodity, as far as global turn over is concerned.

On the climate side also more indices should be included. Monsoon indices are surely candidates, the same holds for the QBO (Quasi Biennale Oscillation, a stratospheric phenomenon with large scale impact) and the SOI (the atmospheric part of the ENSO cycle). Furthermore it might be interesting to include ocean subsurface measurements.

In this study we used climate indices that represent sea surface temperature and atmospheric circulation anomalies. It may be an advantage to take the full fields and extract the dominant indices with the same pattern recognition methods (EOF, SVD) as used in this study.

On the forecasting side the next step must definitely be the use of real climate predictions. Climate prediction centers must be contacted to get such forecasts. Nowadays so-called ensemble predictions are carried out to obtain probabilistic forecasts. Applying our statistical methods to such forecasts yields probabilistic price predictions. Beside the prediction of the actual price these forecasts provide also information about the uncertainty of the forecast. Together with cost/loss optimization methods probabilistic forecasts enable the optimization of business strategies and the estimation of the mean value of a forecast system (this will be explained in an extra paper).

7. Conclusions

The influence of global climate variability on the prices of nine different commodities as noted at the New York commodity exchange was investigated. Pattern recognition and multivariate linear and nonlinear statistical modeling methods were combined.

Statistically significant relations between climate variability and the price of some commodities could be identified. These are soybean oil, soybean, soybean meal, corn, and wheat. The main predictors are sea surface temperature variations in the Pacific and the Atlantic. Among those the El Nino / Southern Oscillation phenomenon clearly dominates.

The climate-induced variations can explain up to 60% of the total price variability, depending on the commodity. These portions are big enough to base business strategies upon them. The residual signal (the part not explained by climate) is at least for some commodities red noise, which implies that there is no other external, predictable mechanism influencing the prices of those commodities.

Beside a range of statistical analyses a jackknife test (not presented in this paper) was carried out to simulate as closely as possible real forecast situations. A jackknife test excludes artificial skill and thus gives a good estimate of the achievable predictive skill of a forecast system. Correlation skills of up to 0.72 and explained variances of up to 50% were found. This confirms the robustness of the found relations and indicates that no over-fitting was done.