Levy Carciente, Sary; Sabelli, Hector; Jaffe, Klaus
Complex patterns in the oil market

COMPLEX PATTERNS IN THE OIL MARKET

SARY LEVY-CARCIENTE, HECTOR SABELLI and KLAUS JAFFE

ommodity prices are known to be very difficult to predict (Adams, 2003). Early studies in this area assumed that they followed a 'random walk' described by Brownian motion, and this stochastic behavior plays a central role in the models for valuing their contingent claims and in methods for evaluating investments for their generation (Brennan and Schwartz, 1985; Schwartz, 1997, Schwartz and Smith, 2000). A commodity is a fixed physical substance that investors buy or sell, usually via future contracts at the Commodities Exchange Center (CEC). A commodity future contract is a commitment or agreement to buy or sell a specified quantity of a commodity at a specified price in a stipulated future date. The original goal of the future commodity market was to guarantee producers the price of goods or raw material used in production; that is, to act as a hedge for price volatility. However, it became also a scenario for speculators with the aim to capitalize on the volatility of the contracts themselves. These two quite different kinds of participants, hedgers and specula-

tors, make it difficult to predict market behavior.

Yet, different kinds of price analysis, especially those based on methods originally developed by physicists or physical-chemists (Georgescu-Roegen, 1971; Ruelle, 1991; Ruth, 1993; Macrakis, 1997) use new insights to perform the analysis. More recently, the study of economic phenomena by means of tools borrowed from physics is called "Econophysics" (Mantegna and Stanley, 2000). The studies have shown that time series of financial markets contain complex structures that eventually might reveal fundamental characteristics of the markets. For example, Gabaix *et al.* (2003), starting from an empirical characterization of the size distribution of large market participants (mutual funds), showed that a power law, observed in financial data, arises when the trading behavior is performed in an optimal way.

This search for some fundamentals might be particularly relevant for less developed countries, which

are dependent on exports, and especially pertinent for the implications on output and business cycles, in which oil has shown to be a sensitive commodity during the last century. Oil markets are constantly adapting to ever changing environmental, social, economic and political factors (Fama, 1987) and have several properties that characterize complex systems (Sugerman and Sabelli, 2002; Sabelli, 2003). Economic analysts recognize that changes affecting the oil market in the future may destabilize it, eventually causing wild fluctuations in prices. Yet, in the past, oil markets have suffered from quite severe disturbances, and despite these challenges, oil markets have proved surprisingly resilient, so that oil prices have been maintained between limits that differ in less than a single order of magnitude. The question we might ask is if there exist underlying mechanisms or properties of the market that provide it with some structure, giving it such resilience. With this in mind, historic data for oil is studied, using a set of statistical and dynamic methods, including a number of new measures and techniques.

Sary Levy-Carciente. **Economist, Universidad Central de Venezuela (UCV). Master in International Economics (UCV). Ph.D. in Development Studies, Centro de Estudios del Desarrollo (CENDES/UCV). Professor, UCV. Address: Instituto de Investigaciones Económicas 'Rodolfo Quintero'. Res. #1, Piso 3, Ciudad Universitaria, Caracas, Venezuela. e-mail: econofin@cantv.net**

Hector Sabelli. **M.D., Universidad de Buenos Aires (UBA), Argentina. Doctor in Medicine, UBA. Doctor Honoris Causa, Universidad de Rosario, Argentina. Director, Chicago Center for Creative Development, USA. e-mail: Hector_Sabelli@rush.edu**

Klaus Jaffe. **Chemist, Universidad Simón Bolívar (USB), Venezuela. M.Sc. in Biochemistry, Instituto Venezolano de Investigaciones Científicas, Venezuela. Ph.D. in Animal Behaviour, University of Southampton, UK. Professor, USB. e-mail: kjaffe@usb.ve**
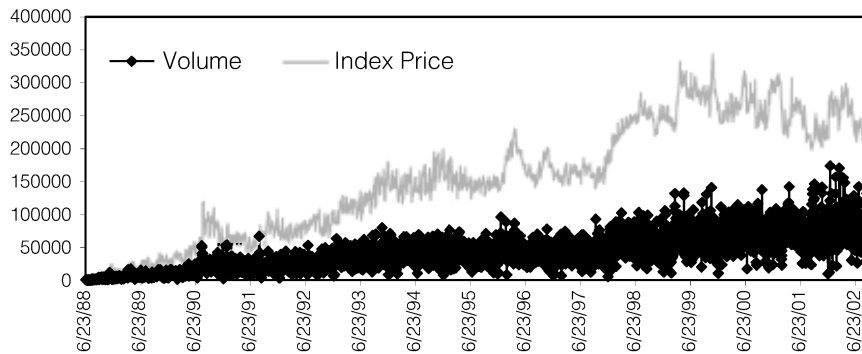
Figure 1. Brent Futures (Jun 23, 1988 - Sept 30, 2002)

Methods

Data from the International Petroleum Exchange (IPE) of London was used: the IPE Brent Oil Index (OI) which is the daily average for the 15 days futures price of Brent crude oil, and the volume of Brent crude oil exchanged every day (IPE, 1988-2002). Data series were from Jun 1988 to Sept 2002. Time series of data were analyzed using the MatLab 6.5 program and an analysis software suite termed the Chaos Data Analyser (Sprott and Rowlands, 2003).
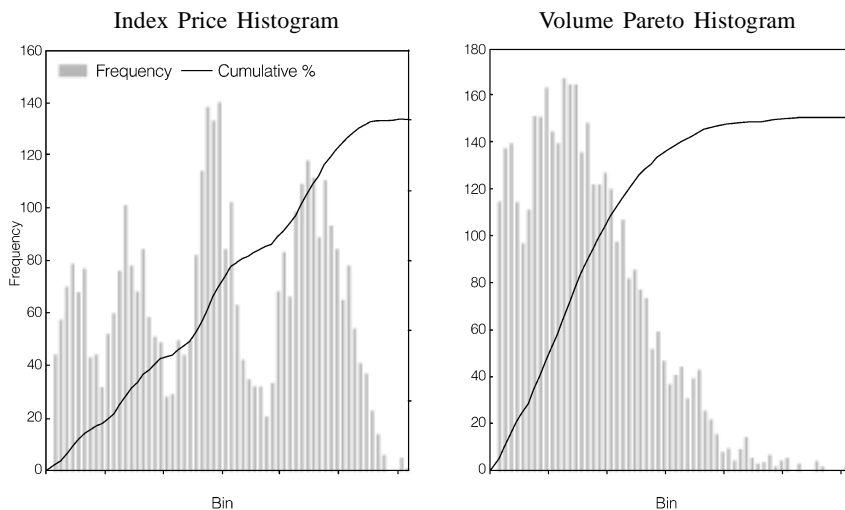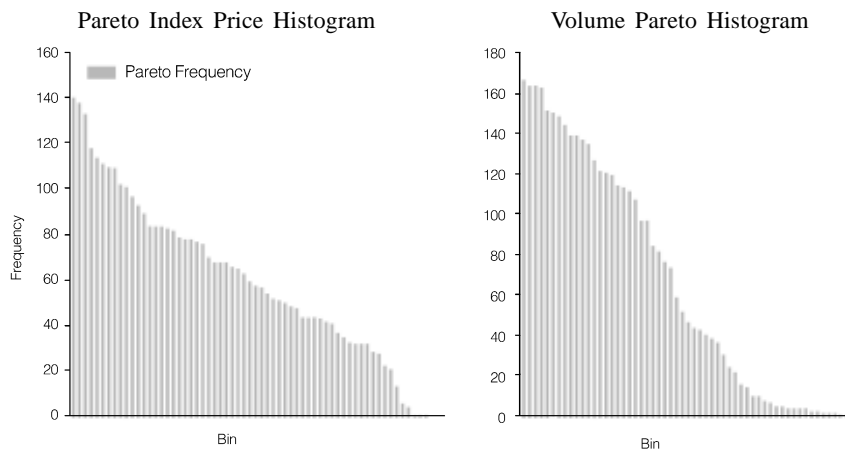

Figure 2. Frequency histograms

Figure 3. Pareto Histograms

Results

Statistical analysis of the oil market behavior

Both the time series behavior for the oil price index and the oil volume of Brent crude show clear increasing trends with irregular fluctuations as presented in Figure 1.

The data for each variable is depicted in Figure 2 by using a relative frequency distribution. The histogram for the oil price index shows an irregular (plurimodal) distribution with four distinct modes, but all of them showed normality. The histogram for traded volume shows an extremely positive asymmetric unimodal distribution.

The Pareto chart, a specialized version of a histogram that ranks the categories from most frequent to least frequent, presented in Figure 3, shows that price index distributions are rather more concave, whereas those for volume are more convex, especially for the least frequent values at the right hand of the plots.

Bivariate Outcome

To depict bivariate data (correlations between prices and volume) a scatter diagram (Figure 4) was used and the Pearson's coefficient was calculated. A correlation coefficient between price index and volume exchanged of r= 0.81 was found (R^2= 0.65, Standard Error= 16929), indicating a strong positive association between variables. The association was much weaker when the data was analyzed for different periods:
1995-1998: r_{yx}= 0.862440357 (strong association)
1999-2002: r_{yx}= 0.440382945 (weak-moderate association)
1999-2003: r_{yx}= 0.084849421 (little, if any, association)

If the scatter diagram of Figure 4 is explored for heterogeneity or clusters, it can easily be observed that data was denser around three points, sug-
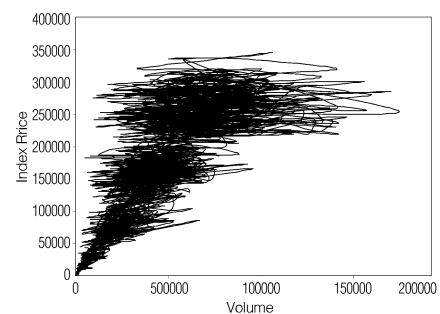

Figure 4. Volume / Index Price 1988-2002

gesting the existence of temporal attractors or stationary states in the diagram.

Oscillations

When using tools for dynamic analysis, more interesting features of the time series were revealed. The consecutive differences in price and volumes are presented in Figure 5, showing the volatility of the series. The volume shows much faster oscillations than the price, and a clear increasing trend. Variability is more irregular for price.

Difference frequency distributions

The relative frequency distribution of differences between consecutive terms (Figure 6) shows that data for volume approach normality, but not that for prices. In both cases, the series show leptokurtosis, being the kurtosis greater for index price (k= 8.314565) than for volume (k= 7.752214).

Pareto dynamics

A Pareto representation for both series of consecutive differences (Figure 7) shows that the differences are markedly asymmetric.

Return map or phase portrait

The return maps for oil price and volume that plot each term of the time series *vs*. its consecutive previous difference (X_t *vs*. $X_t - X_{t-1}$) show a pattern that again differs between price and volume (Figure 8).

The Hurst exponent

Calculations for the Hurst exponent (Peters, 1996) resulted in an H value for the price index of 0.333, and for volume of 0.075. As Hurst exponents are different from 0.5, observations in price and volume time series are not independent, and both observations carry memory. As both are <0.5, the systems are antipersistent, or time series are ergodic or 'mean reverting'. That is, if the system was down the last period, in the next it is more likely to be up. As volumes traded have a Hurst exponent closer to 0, the volatility of this series is much higher than the one found in a random Brownian motion, because it would consist of frequent reversals. At larger time scales, the Hurst exponent tends to be more Brownian and in both cases 'memory is
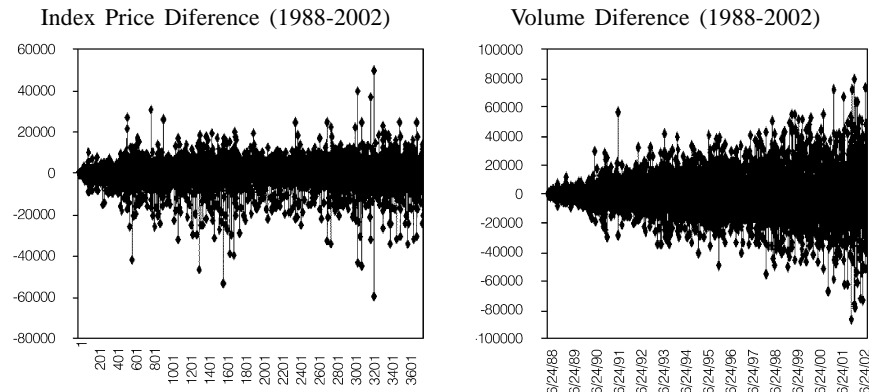
lost' after about 10 years, revealing cycles of this length (Figure 9).

Conclusions

The results show that the oil market can be analyzed with tools borrowed from the physical sciences. The main findings from this exercise may be summarized in three distinct fundamental conclusions:

1- The variability and dynamics of the price index differs from that of the volume of oil exchanged. The average price index increases in time, whereas the average volatility of oil volumes exchanged increases in time. This can be clearly seen in Figures 1, 5 and
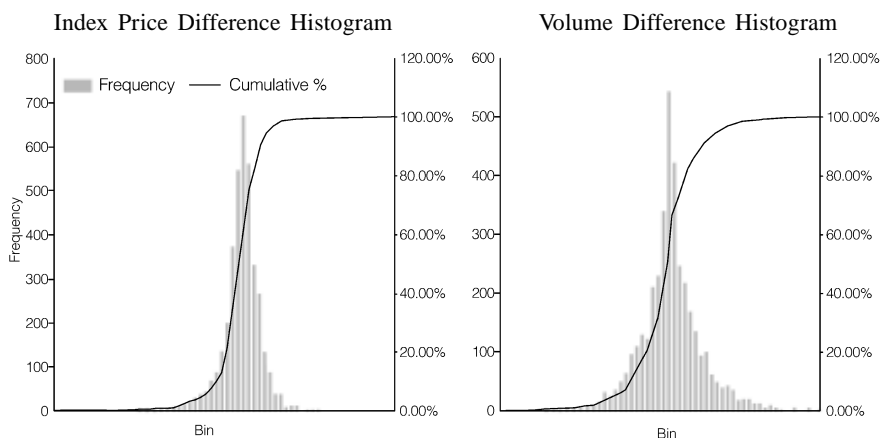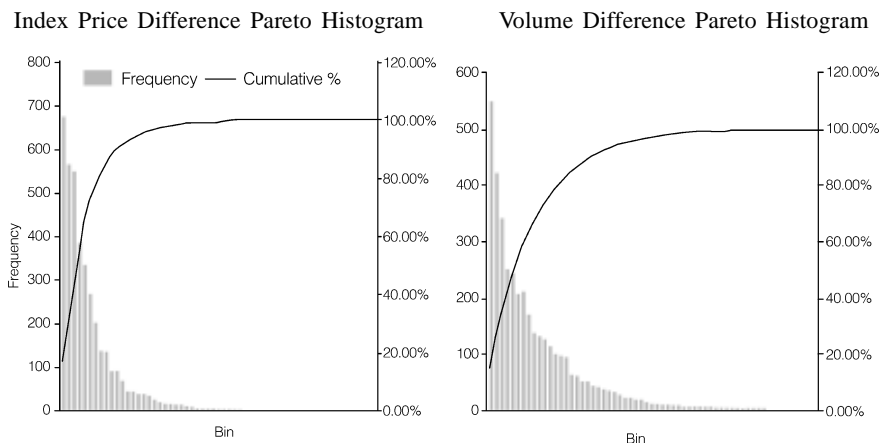
Figure 5. Consecutive Differences

Figure 6. Consecutive Difference Histogram

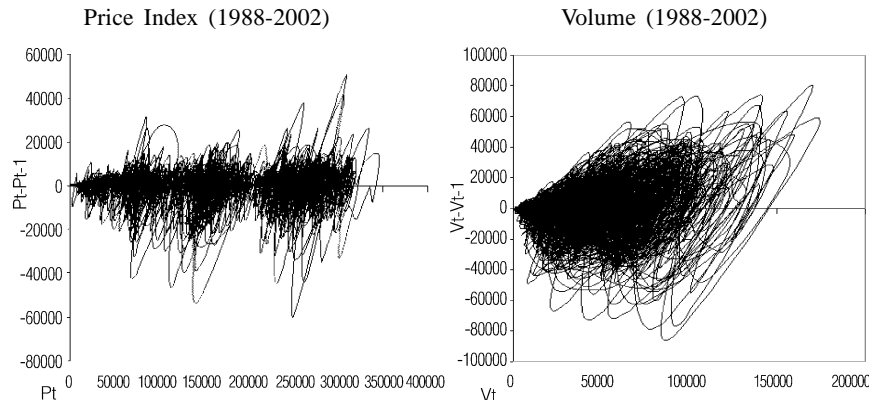Figure 7. Consecutive Differences Pareto Histograms

Price Index (1988-2002)

Volume (1988-2002)

Figure 8. Phase Portraits

H = 7.538926E−2
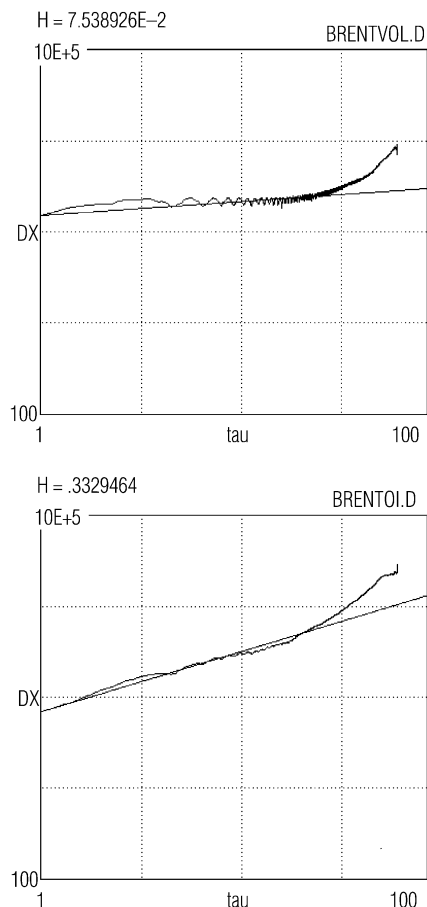
BRENTVOL.D

H = .3329464

BRENTOI.D

Figure 9. Hurst Exponent

8. Thus, prices and volumes seem to be perceived psychologically differently by traders and, thus, their dynamics follow different rules. Increased volume volatility in more recent times might indicate an increased participation of more distinct traders, or the increased dominance of a few traders in the market. The increase in the average oil price future index might just reflect the inflation of the underlying currencies involved, as in constant terms, oil prices have been rather in decline (OPEC, 2002).

    2- Changes in prices are asymmetric in time. Large increases in oil prices are less likely to occur than large drops in the oil price index. This asymmetry can be clearly seen in Figures 6. This is an additional feature that differentiates prices from volumes. As shown in Figures 3 and 7, volumes traded do not show the skewedness and asymmetry of prices. This result shows that the risk assessment for oil traders is asymmetric respect to prices. This asymmetry might be explained by known features of our bounded economic rationality, such as an excess fear to losses (Kahneman and Tversky, 1979; Shefrin and Statman, 1985; Kahneman, 1994). An alternative explanation to this asymmetry is that it might arise from the fact that sellers are more likely to panic or have more constraints than buyers, making it more likely for large drops in prices to appear in the time series than large increases in prices.

    3- Values of the price index cluster in time, showing the existence of specific historic phases in oil price index. Such historic phases could not be seen in data from oil volumes exchanged. This clustering of time-phases is evidenced in Figures 2, 4 and 8. They suggest that the oil market somehow reaches steady states (i.e. temporal unstable "equilibria" as defined by Nicolis and Prigogine, 1977) which are disrupted from time to time, probably by external factors. However, it is surprising and highly significant in economic terms that such steady states exist and that they are maintained during significant periods of time.

REFERENCES

Adams G (2003) *Commodity prices: Current perspective.* Spring Meeting of Project LINK. New York, EEUU. http://www.chass.utoronto.ca/link/meeting/papers/commodity200304.pdf

Brennan MJ, Schwartz ES (1985) Evaluating natural resource investments. *J. Business 58*: 135-157.

Fama EF (1987) Commodity Future Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. *J. Business. 60*: 55-73.

Gabaix X, Gopikrishan P, Plerou V, Stanley HE (2003) A theory of power-law distributions in financial market fluctuations. *Nature 423*: 267-270.

Georgescu-Roegen N (1971) *The Entropy law and the Economic Process.* Fundación Argentaria. Madrid, Spain. 545 pp.

IPE (1988-2002) Brent Oil Index and Daily Crude Exchange. International Petroleum Exchange. www.epi.com.uk/algomas

Kahneman D, Tversky A (1979) Prospect Theory: An Analysis of Decisions Under Risk. *Econometrica 47*: 263-269.

Kahneman D (1994) New Challenges to the Rationality Assumption. *J. Instit. Theor. Econ. 150*: 18-36.

Macrakis MS (1997) *Scarcity's Ways: The Origins of Capital. A Critical Essay on Thermodynamics, Statistical Mechanics and Economics.* Boston Studies in the Philosophy 176. Kluwer. Dordrecht, Netherland. 230 pp.

Mantegna RN, Stanley HE (2000) *An Introduction to Econophysics: Correlations and Complexity in Finance.* Cambridge University Press. New York, USA. 148 pp.

Nicolis G, Prigogine I (1977) *Self-organization in Nonequilibrium Systems.* Wiley. New York, USA. 491 pp.

OPEC (2002) Annual Statistical Bulletin. (Table 73, p.119; Graph 54, p.123).

Peters EE (1996) *Chaos and Order in the Capital Markets.* 2nd ed. Wiley. Hoboken, USA. 274 pp.

Ruth M (1993) *Integrating Economics, Ecology and Thermodynamics.* Kluwer. Netherlands. 264 pp.

Ruelle D (1991) *Chance and Chaos.* Princeton University Press. Princeton, USA. 195 pp.

Sabelli H (2003) *Bios, creative organization in economic, biological, and meteorological data.* International Conference on Advances in Internet, Processing, Systems, and Interdisciplinary Research. Electronic Publication IPSI-2003.

Shefrin H, Statman M (1985) The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, *J. Finance 40*: 777–792.

Schwartz ES (1997) The Stochastic Behavior of Commodity Prices: Implications for Valuation and Hedging. *J. Finance 52*: 923-973.

Schwartz ES, Smith JE (2000) Short Term Variations and Long Term Dynamics in Commodity Prices. *Manag. Sci. 46*: 893-911.

Sprott JC, Rowlands G (2003) *Chaos Data Analyser, CDA.* http://sprott.physics.wisc.edu/cda.htm

Sugerman A, Sabelli H (2002) Novelty, Diversification and Nonrandom Complexity Define Creative Processes. 12th International Congress of the World Organization of Systems and Cybernetics, and 4th Workshop of the International Institute for General Systems Studies. Pittsburgh, March 2002.