TCS™ Market Timing

- Financial Markets are characterised by **radical uncertainty** and **complexity**.
- This calls for an **alternative paradigm** and its **associated tools** to improve the prediction of the future behaviour of financial assets: Econophysics, Fractal Markets Hypothesis, Thermodynamics, Entropy, Information Theory…

"In recent years the point of view in which financial markets are defined has started to change. A new aspect is the consideration of financial markets as complex systems. They are systems consisting of many interacting agents, where these interactions are of a highly nonlinear nature. This enormous amount of data allows a detailed statistical description of several aspects of the dynamics of asset price in a financial market. The results of studies based on these data show the existence of several levels of complexity in the price dynamics of a financial asset. An alternative way of analyzing markets is therefore by using the concepts of thermodynamics."

"The Study of Markets and Prices, - The Thermodynamics Approach" -Electronic Journal of Theoretical Physics (S. Prabakaran, and K.Alkhathlan, 2010)

"This illustrates very well the fact that those systems that can be described by non-linear equations, as is the case in weather forecasting, can exhibit surprising and unexpected behaviours, with sudden jumps to states that previous experiments, carried out in regimes where the non-linear equations could be approximated by linear ones, could not help anticipate."

Translated from https://www.futura-sciences.com/planete/actualites/rechauffement-climatique-rechauffement-climatique-vers-disparition-nuages-13-c-plus-75158/

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THEORETICAL FRAMEWORK – TCS™ MARKET DNA

The Efficient Market Hypothesis (EMH) introduced by Fama in 1965 has been a paradigm of economic and finance theory for many years. It states that the current price of an asset fully reflects all available relevant information and that new information is immediately incorporated into the price. EMH assumes investors to be rational, orderly, and homogeneous, which leads to simple linear differential equations with one solution. However, empirical analysis demonstrated that this paradigm is questionable, there is complexity and disorder in financial markets, and investors are heterogeneous and subject to different time horizons and constraints.

Edgar E. Peters makes a bridge between EMH and the Fractal Market Hypothesis (FMH) in two books: Chaos and Order in the Capital Markets (1991) and Fractal Market Analysis (1994). In his first book, Peters loosens unrealistic assumptions of EMH, generalizes the view of market behavior, and defines capital markets as nonlinear dynamic systems, which are characterized by i) **long-term correlations and trends** (feedback effects), ii) **erratic behavior** at certain times and under certain conditions, iii) **self-similarity**, a time series of returns looks the same at smaller increments of time and has similar statistical characteristics (fractal structure), and iv) less reliable forecasts, the further out in time we look (sensitive **dependence on initial condition**).

So if EMH may appear as a reasonable assumption at macro level over a long time horizon where financial markets exhibit global determism, it does not hold over shorter periods of time where local randomness caracterised by random walks, jumps and succession of quiet and hectic periods are observed. For this scale, the FMH and the theories of complex systems are more revelant to understand the dynamics of financial markets.

As they exhibit all the attributes of complex dynamic systems, financial markets have been attracting over the past years an increasing attention amongst physicists, computer scientists, and other researchers devoted to studies of complex systems. Complementing traditional statistical and econometric methods, an interdisciplinary field of research named "econophysics" has emerged, advancing techniques that originate from statistical physics in order to shed new light on the phenomenological observations. Physicists have devoted considerable effort to answer such questions by searching for a collection of ’universal laws’ that can effectively describe financial markets and their dynamics. Amongst the most important findings are the presence of scale-invariance and long-term memory in asset prices, previously unrecognized in both in finance and economics. Econophysicist claim that models formed from observations in financial data, rather than theoretical conceptions, are more ’realistic’ and more accurately represent underlying phenomena.

As a result, one can use frameworks found in other domains than finance to better understand the dynamics of financial markets. For example, both thermodynamics and information theory deal with complex non-linear systems that present analogies with financial markets. The common factor across all these fields is the notion of entropy. In classical thermodymamics, entropy measures the degree of disorder of the molecular motion caused by increasing heat (or energy) in an isolated system. In information theory, Shannon entropy refers to the average quantity of information encoded in a message. In financial markets, information indeed represents the “energy” of the system and the quantity of information - or entropy - needed to model the behaviour of the system

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is time-varying. When entropy is low, the number of parameters required to model the system is lower and the predictability (or probability of accurate forecasting) increases. When entropy is high, the energy quantity of the system does not allow for prediction as too many parameters are at play. The two first laws of thermodynamics (principle of conservation of energy and never-decreasing entropy) can also be applied to financial markets.

As a consequence, predicting financial markets with a high degree of probability is a very challenging if not impossible task. As outlined by B. Mandelbrot (" The Misbehavior of Markets" 2004), the complexity inherent to financial markets prevents any attempt to model them in an exhaustive and continuous manner.

This illustrates very well the fact that those systems that can be described by non-linear equations, as is the case in weather forecasting, can exhibit surprising and unexpected behaviours, with sudden jumps to states that previous experiments, carried out in regimes where the non-linear equations could be approximated by linear ones, could not help anticipate.

The Market DNA algorithm is inspired by both the work of B. Mandelbrot on multifractals and by the theories of non-linear dynamic systems. It aims to take advantage of the successions of low and high entropy regimes observed in financial markets at different time scale to determine patterns and entry and exit points in time series.

The main assumptions / characteristics of the TCS Market DNA are:

- Financial markets are complex non-linear systems that tend towards maximum entropy and self-organize.
- Entropy represents the quantity of information needed to be more confident about modelling the behavior of financial markets. Periods that are subject to many repeated patterns will tend to have a lower entropy than those with fewer occurrences. The longer the time horizon for prediction, the less precise the information will be, and the most likely entropy will increase.
- The variation in volatility in price series can be used as a proxy for entropy. Volatility is the second-order moment of the prices distribution and exhibits short-term autocorrelation (volatility clustering) that can be used to determine the state of equilibrium and the ‘long’ memory of the system.
- When the quantity of information required to explain the behavior of the system is low (i.e. negligible entropy), the system will tend to fluctuate around its equilibrium. This equilibrium can then be described empirically using the initial conditions (long memory feature inherent to complex systems) deformed by the level of entropy observed at that point of time.
- Some of these parameters - or “initial conditions” - are idiosyncratic to the market on which they are observed as they describe a state of equilibrium of the system before information gets perturbed by increasing entropy. They have been calibrated on historical data by measuring success rates at a given probability level for the lowest level of entropy as possible.
- The scale invariance property of the FMH allows to determine the correspondence (a fractal dimension factor) when moving from one time scale to another.
- Entropy is a discontinuous notion and therefore the model is bounded with thresholds and caps to limit the risk of inaccurate prediction.

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Decoding the Market DNA algorithms in a nutshell

The algorithms are reasonably simple to understand once one gets a sense of the three sequential steps:

1. Determination of the entropy production at each time step. This is the key part of the algo as this is what will be used for the auto-calibration throughout all subsequent steps (deformed periods aka fractal segments)

Entropy production is measured by the exponential of the ratio between the instantaneous volatility (i.e.expressed over 1 period resolution) in t and the the instantaneous volatility in t-var periods

$$Entropy\_variation_t = e^{\frac{\frac{histoVolVar_t}{\sqrt{var}}}{\frac{histoVolVar_{t-var}}{\sqrt{var}}}}$$

The cycle objective (profit1) is calculated by multiplying the observed level of volatility at each period by the level of entropy variation to determine the projected level of volatility (i.e. potential profit) for the next period.

$$\boldsymbol{profit1_t} = \frac{histoVolVar_t}{\sqrt{var}} \times Entropy\_variation_t$$

2. De-noising of the series (vol and prices) to obtain smoothed estimates and determine the bounds of the stochastic oscillator (CCI) for the pattern recognition step

3.a. Medium Term Pattern (MT DNA) recognition algo (DNA: 1, 0, -1) based on the CCI (Standard) with dynamic conditions to determine actual long and short cycles

3.b. Long Term Pattern (LT DNA) recognition algo (DNA: 1, 0, -1) based on the Entropy Trend (de-noised by CCI) with dynamic conditions to determine actual long and short cycles

3.c. Aggregating LT and MT DNA, the Market DNA code will be defined (2, 1, 0, -1, -2)

Assuming the multifractal nature of time series, the first step is to “decode the fractal property” (DNA) of the time series considered and determine fractal segments at different time scales that exhibit similar probability distributions (scale invariance property of fractals). This is done through numerical analysis using machine learning techniques and consists in an optimization process that maximizes the probability to predict the next variation in price for a given level of entropy production (refer below for more on entropy production)

Once the fractal dimension has been determined, the probability distribution over a short and long fractal segment is computed. Here we assume that at this time scale (5-minutes spot levels), prices follow the lognormal distribution of a standard Wiener process (see E. Bacry papers on multifractals). Jumps will only be detected by sudden variation in differential entropy.

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Why the need to use the concept of entropy to predict future patterns in financial markets?

In information theory, entropy is a measure of the quantity of information delivered by each message (bit of information). In thermodynamics, it is a measure of the order or disorder of the molecular motion caused by increasing heat (or energy) in an isolated system. In financial markets, it is the quantity of information conveyed by each increment in prices (in other words, what new information we can learn from price movements). So as entropy increases, the higher the noise, and the lower the information we receive per "message" (i.e. price movements) and therefore the lower the probability to forecast accurately the next price pattern.

Besides, Nobel Prize Ilya Prigogine's work on dissipative structure is interesting if we make the parallel with financial markets. It shows that in the second law of thermodynamics, complex systems tend towards maximum entropy until they reach an equilibrium state. It is therefore crucial to precisely measure variations in entropy to determine if the system is at a local equilibrium or if entropy (i.e. disorder) increases.

How to measure entropy production?

Two ways here: we can either keep it "simple" and use a proxy (i.e. a heuristic computation to assess only the level) or go for a more precise approach based on the canonical entropy calculation from the Shannon equation.

For the simpler heuristic approach we assume two log-normal probability distributions (characterized by their second moment): one over the short fractal segment and the other over the longer segment (as determined by the initial calibration). That's why we first compute the volatility over these two periods (first calculation in the algo) as a proxy for these probability distributions. We don't need to assume the full distribution here, as we are not interested in all the parameters for determining the entropy differential but by the ratio between these probability distributions (i.e. annualized standard deviations here)

As per the FMH and the scale invariance property, even though the probability distributions have different parameters (standard deviation and mean) over different fractal segments, the ratio between the two probability distributions is assumed to be invariant if entropy production is zero.

This concept of proportionality of scaled probability distributions in multifractal price diffusion is not new and was discussed in a few papers that also make the link with entropy production.

Of course, as markets are dynamic systems, entropy production is rarely equal to zero (in that case it would be much easier to forecast time series…). Entropy increases under the assumption that financial markets behave like dissipative structures (i.e. they tend towards maximum entropy and self-organize). That's why the proxy measure of entropy production is based on the exponential function (that maximizes entropy) of the ratio between two probability distributions measured over a short and long fractal segments to measure each increment in the production of entropy in order to increase measurement precision.

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Also as mentioned previously, one could prefer using the canonical Shannon entropy calculation module to increase precision and have fewer assumptions, compared to the proxy entropy measurement.

Let X be a random variable with a probability density function f(X) whose support is a set. The differential entropy h(X) is defined as: (source:Wikipedia).

$$h(X) = -\int_{\mathcal{X}} f(x) \log f(x)\, dx$$

We then do this calculation once again to take into account the new market conditions and “adjust” the short fractal segment determined in the machine learning calibration phase with the level of instantaneous entropy production we just measured. Indeed B. Mandelbrot in «The Misbehavior of Markets" (2004) observed that trading time is not linear and relative to the speed of the market (entropy variation here measures the derivative of this speed and thus the deformation of time). The higher the entropy production, the longer the observation window required to understand the information provided by price movements.

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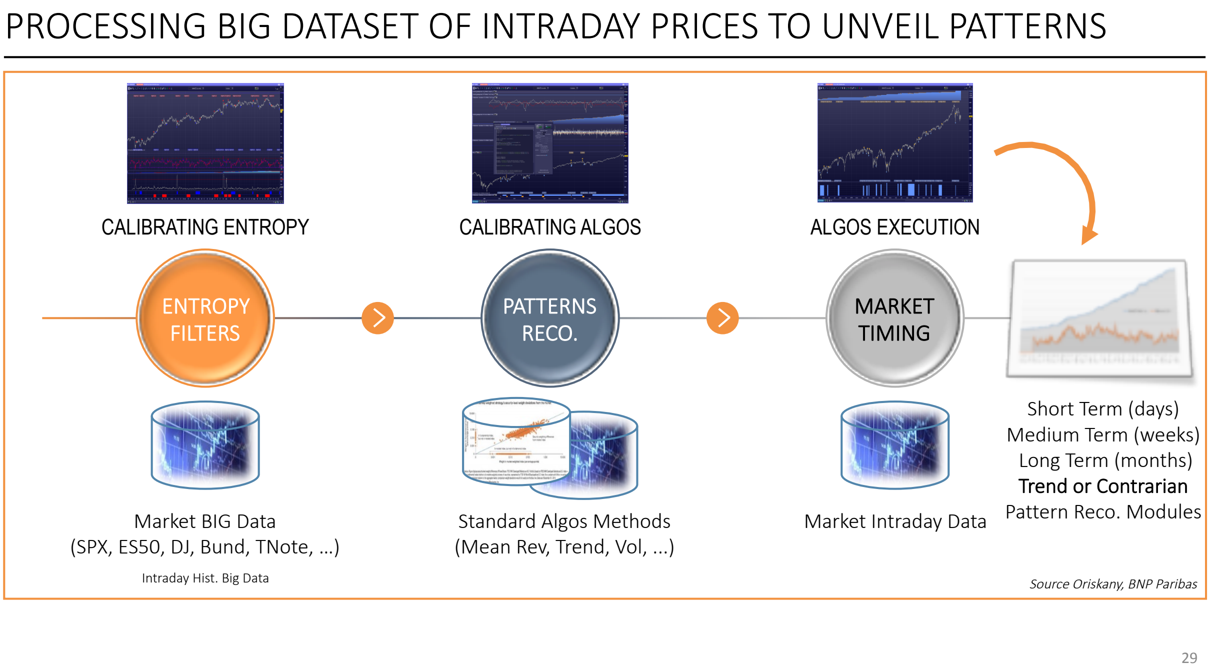
PROCESS ILLUSTRATION



For statistics and further information, please refer to “TCS Core LEM FlagShip Statistics & Presentation – 2019”.

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