# *MEASURING IRREGULAR CYCLES IN ECONOMIC TIME SERIES*

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**Overview**

Dynamics play an important role when analysing macro- and microeconomic market phenomena. In many markets, both overlaying market and time-varying dynamics exist simultaneously. Identification of these market dynamics is crucial and no standard procedure for detection exists. In this paper we introduce and investigate an adaptation of an endogenous structural break test [Bai and Perron (1998, 2003)] for detecting at the same time simultaneous, overlaying as well as dynamic, time-varying market dynamics. In combination with rolling regressions applied to filtered time series, this approach allows to disentangle these different dimensions of time series analysis. This is useful in both macroeconomic growth, inflation, or business cycle analysis and microeconomic analysis of temporally varying short-term behaviour of market participants. We demonstrate the approach using a time series of hourly electricity prices and compare it to other methods common in the field of structural time series analysis (traditional Bai and Perron endogenous structural break test, Markov Regime Switching, Fast Fourier Transformations).

**Methods**

We combine a structural break test with rolling regressions and filtering. This enables us to endogenously identify and disentangle simultaneously overlaying (vertical) and time-varying (horizontal) dynamics in time series. The approach uses a combination of rolling regressions and the classical Bai and Perron (1998) endogenous structural break test applied to a filtered, smoothed time series. Beginning at the lowest imaginable frequency, a simple moving average is applied to the time series followed by the rolling regressions memorizing the structural break dates of each of the rolling tests. Clustering of these break dates is then used to identify the definite breaks on the respective frequency. The distribution of section lengths between the breaks helps identifying the dominant dynamics. This procedure is repeated successively for higher frequency levels down to the fastest dynamic. Thereby, we disentangle overlaying characteristics on different frequency levels from each other while differentiating between dynamic, time-varying characteristics on the respective frequency level.

**Results**

The following diagrams illustrate the differences between the compared methods. The solid black line depicts the electricity prices of March 2010 in all of the four diagrams. The rectangle areas indicate breaks and state changes - or dynamic changes. They extend below or above the mean of the time series depicted by the fine horizontal constant line. Every time the indicator line crosses the mean line, the respective method found a state switch and the rectangle areas between the lines change their position from below to above and vice versa. The magnitude of the indicator line has no meaning, but is solely used to indicate breaks.

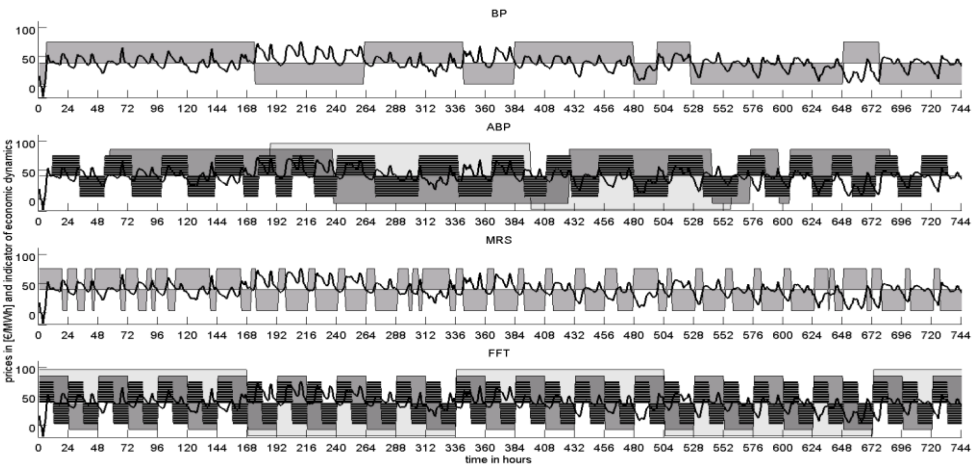


Diagramm: EEX day-ahead electricity prices, March 2010; identified dynamics according to the different approaches (a) Bai and Perron endogenous structural break test, b) Adapted Bai and Perron test, c) Markov Regime Switching, d) Fast Fourier Transform)

The BP and MRS do not explicitly differentiate between different frequency levels of dynamics, or in other words: In a one-shot procedure they judge all dynamics according to one single decision criterion—the reduction in residuals. These dynamics will only be identified if and only if they are sufficiently important with respect to this criterion. In contrast, the ABP and FFT find a multiplicity of dynamics, because they decompose the time series vertically. Three of these major dynamics are examplarily depicted.

## 1. Conclusions

This article adapts the endogenous structural break test by Bai and Perron (1998) and successively applies it in rolling regressions in combination with filtering of a time series at different frequency levels. This approach offers richer information than classical BP, MRS, and FFT applications to the time series, because of the cumulation of break partitions calculated on the different frequency levels. The ABP disaggregates the time series in a horizontal, time-varying dimension - similar to MRS and, of course, BP - as well as in a vertical, overlaying dimension - similar to the FFT.

The ABP allows the researcher to differentiate between market dynamics on various levels. This might be of use in e.g. business cycle analysis, where it is important to disentangle characteristics of one time series on different, previously not known, frequency levels. Thereby, the proposed adaptation could help to identify time-varying cycles. So far, researchers mostly either use exogenous, constant cycle definitions or employ MRS buying its inappropriate features for the analysis of overlaying and time-varying time series characteristics described in this article (Chauvet and Hamilton 2005). On a short-term, more microeconomic-based individual level, this dynamisation approach might help to identify time-varying behaviour in markets of high frequency interaction such as internet markets or markets with cyclical regularities or asymmetric cost pass-through, which alter over time (Peltzman 2000). In this regard, it can also help to disentangle these short-term characteristics of the time series from overlaying, long-term characteristics. In applied work, it can then be used to construct better screening instruments for collusion detection (Abrantes-Metz et al. 2006, Harrington and Chen 2006) or in the important field of market delineation, which is important in view of the more (short-term) behaviour based “more economic approach”.

This approach should be extended in various dimensions such as offering the possibility to cope with possibly cointegrated explanatory variables (Kejriwal and Perron 2008, Bataa et al 2013). Moreover, a more complete picture with regard to variations of this adaptation approach described in section 4 would be desirable as well as a more differentiated picture with regard to a comparison with modified versions of the other methods..

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