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Jump point detection using empirical mode decomposition

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ABSTRACT

Real estate is an important form of investment in Hong Kong. Recent researches on the analysis of real estate market have revealed that jump points in the housing price time series play an essential role in the Hong Kong economy. Detecting such jump points thus becomes important as they represent vital findings that enable policy-makers and investors to look forward. In this paper, we propose a jump point detection methodology, which makes use of the empirical mode decomposition algorithm and a derivative-based detector, to detect jump points in the time series of some housing price indices in Hong Kong. Experimental results reveal that our proposed method has a superior performance and outperforms the current state-of-the-art wavelet approach.

1. Introduction

Real estate is one of the most important forms of investment and plays an essential role in the economy of Hong Kong. It is believed that changes in housing prices would influence consumer price inflation and have substantial impact on the economy, which subsequently may also affect the competitiveness of Hong Kong. As Hong Kong has adopted a free market economic system and its economy is governed under positive non-interventionism, the level of government interventions in the economy is comparatively low in the world. Resulted from high degree of economic freedom, the real estate market in Hong Kong is basically market-driven and dependent on demand and supply. Nevertheless, the Hong Kong government is the only supplier of new developable land, it has far more ability to influence the housing prices than aggregate demand. The short of land and housing would lead to the rise in housing prices and rents. Thus, land supply is one of the major factors affecting the housing prices. For instance, the Hong Kong government introduced detailed measures to improve the flexibility of land use and land supply in March 1994, which made the property prices drop by 20%–30% in 1994–1995. In addition to some other factors affecting the market downturns, we believe that the government's land use policies also have had impact on the real estate market. More recently, the Hong Kong government has gradually been introducing various "cooling" measures to cool the overheating real estate market and stamp out short-term speculation. For instance, stamp duty was raised to 4.25% for properties worth more than HK$20 million since February 2010; My Home Purchase Plan was introduced and Special Stamp Duty (SSD) was imposed in November 2010; the Buyer's Stamp Duty (BSD) for non-permanent residents and foreign companies was introduced in October 2012; and the Double Stamp Duty (DSD), which doubles the stamp duty rate for property transactions, was announced in February 2013. These measures appeared to have temporarily cooled down the real estate market to some extent.

Many studies in the literature indicated that housing prices in Hong Kong are subject to international and regional economic events. For instance, due to the Asian financial crisis began in early 1997, Hong Kong suffered an economic recession and the real estate market was badly hit with property prices dropped by more than 40% between the last quarter of 1997 and the last quarter of 1998. Given the importance of real estate in Hong Kong economy, it is essential to study what drives the changes in Hong Kong's housing prices and how real estate market is influenced by international and regional economic events.

In the studies on real estate market, it is well known that housing prices are influenced by many key factors such as interest rate (mortgage rate), land supply and inflation rate (see, for example, Tian and Ma, 2009; Tsatsaronis and Zhu, 2004). Thus many researchers proposed various statistical methodologies for modeling housing price measurements and assessing the importance of these factors. However, we remark that jump points may occur in financial and housing price measurements that will affect the overall analysis of the time series. Jump points, sharp or abrupt changes are typically related to some regional or international events which are possibly driven by government policies and economic events, and thus, detecting and identifying these sharp changes are vital

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since they reveal important findings that enable policy-makers and investors to look forward. Since such sharp changes may be caused by a mixture of information and noise, it is difficult to observe them directly in the time series. Hence the detection of these sharp changes has drawn much attention from researchers and practitioners.

Motivated by the recent researches on jump point detection, the aim of this paper is to propose an effective approach for identifying and detecting jump points in the time series of Hong Kong housing price indices. In the proposed method, we apply the empirical mode decomposition (EMD) (Rilling et al., 2003, 2007; Huang and Shen, 2005) to decompose a given signal[1] into a set of sub-signals. A series of reconstructed signals are then obtained by sub-signals concatenation. Finally, the jump points are detected based on the rate of change in each of the reconstructed signals. The merits of our approach are threefold. First, adaptive basis functions are used in the decomposition process that leads to an effective reconstruction of the original signal, which can enhance the detection of jump points. Second, a high-level derivative detector is proposed that can improve the detection performance for a highly nonlinear and fluctuated signal. Third, our method does not introduce any sensitive parameter. Comparative experimental results show that our method outperforms the wavelet approach in Hui et al. (2010).

This paper is organized as follows: we are providing a literature review in the next section, presenting the proposed jump point detection methodology in Section 3, reporting experimental results in Section 4, which is followed by the conclusion in Section 5.

2. Literature review

2.1. Applications of jump point detection

The detection of jump points, sharp or abrupt changes (for simplicity, we shall refer all sharp or abrupt changes to as jump points hereafter) has been applied successfully in various fields such as quality control, economics and finance, signal and image processing, and engineering. In Willsky and Jones (1976), the authors demonstrated that jump point detection is useful in the design of failure detection and compensation systems. Basseville and Nikiforov (1993) discussed the theory and applications of jump point detection in quality control, navigation system monitoring, seismic data processing, segmentation of signals and vibration monitoring of mechanical systems. Some studies discuss the applications to stock data, exchange and interest rate series. For instance, Ip et al. (2004) proposed a computing algorithm to detect jump points of the daily exchange rate of US Dollar against Deutsche Mark. Hillebrand and Schnabl (2006) and Ito (2003) identified jump points in the exchange rate series to study the impact of Japanese foreign exchange intervention. Lavielle and Teyssière (2006) detected jump points in the multivariate series of daily stock indices returns while Strikholm (2006) applied a sequential method to investigate and determine the number of breaks in the US ex-post real interest rate series. More examples on the applications of jump point detection in stock exchange data can be found in Wang (1995) and Arago-Manzana and Fernandez-Izquierdo (2007). The jump point detection is also applicable to the study of crude oil markets (see, for example, Kang et al., 2011). More recently, Hui et al. (2010) detected jump points in the time series of private domestic price indices in Hong Kong. They further investigated the effects of various economic events on four Asian office markets (Hui et al., 2013) (including Beijing, Shanghai, Hong Kong and Singapore) by detecting the jump points.

[1] The terms "signal" and "time series" are used interchangeably in this paper.

2.2. Methodologies of jump point detection

Various approaches for the detection of jump points have been extensively studied in the literature. Muller (1992) adopted a nonparametric regression approach to obtain weakly consistent estimators for the locations of jump points and the corresponding jump sizes. Yin (1988) proposed a detection method for the number, location and magnitudes of jumps of a regression function in the presence of noise. While the aforementioned methods work well, satisfactory results are obtained by manually selecting an appropriate regression kernel. We remark that a small kernel will lead to spurious jump point locations whereas a large kernel may not detect jump points with relatively small jump sizes. Based on the sequence of parameter constancy tests in the smooth transition regression framework, a sequential method was used in Strikholm (2006) for determining the number of breaks in a piecewise linear structural break model, which breaks the time series into a number of polynomial functions. In addition, Yang and Song (2014) proposed a polynomial spline approach for jump point detection and the estimation of the discontinuities of regression functions. Although these methods provide a sound mathematical theory that underpins the validity of the framework, we note that their methods may miss the jump points with small jump sizes. Moreover, some of the detection methods perform well only for a data set with moderate size.

In addition to the approaches mentioned above, a time-frequency transformation method is also popular in the literature. Lombard (1988) applied Fourier transform to extract details from the signal. With the use of Fourier analysis, jump points could be detected but their locations (i.e. time) cannot be identified. In addition, some jump points may be missed due to the smoothness of the Fourier basis function. To remedy the shortcoming of Fourier transform, Hui et al. (2010) presented a wavelet method with non-smooth Haar wavelet for detecting jump points in the time series of the private domestic price indices and stock price index. They found that jump points detected by the wavelet approach reflect the announcement of regulations/policies or some regional/international events. With reference to the wavelet approaches in Ip et al. (2004) and Donoho and Johnstone (1994), Hui et al. (2013) employed an improved nonparametric wavelet model to detect jump points in the Asian office markets. Although wavelet approaches usually achieve promising results, the major drawback is that it adopts a fixed basis function which may not approximate signals very well.

3. Jump point detection

One of the main characteristics of a jump point in a time series is its sharp changes (ascent or descent) in a consecutive time period, which can be detected by measuring its rate of change. A larger rate of change implies a sharper change and vice versa. Our strategy to detect a jump point from the complicated real-world time series involves the following two stages. We first employ the EMD algorithm to obtain a set of the smoothed versions of original signal. Then we detect jump points by measuring the rate of change in each of the smoothed signals.

3.1. Empirical mode decomposition

Empirical mode decomposition (EMD) aims to decompose a given signal $x(t)$ into n elementary sub-signals (Rilling et al., 2003; Huang and Shen, 2005) as follows:

$$x(t) = c_1(t) + c_1(t) + \cdots + c_n(t) + r(t)$$