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Risk Estimates of Structural Changes in Freight Rates*

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해상운임의 구조변화 리스크 추정

김현석

Abstract

This paper focuses on the tests for generalized fluctuation in the context of assessing structural changes based on linear regression models. For efficient estimation there has been a growing focus on the structural change monitoring, particularly in relation to fields such as artificial intelligence(hereafter AI) and machine learning(hereafter ML). Specifically, the investigation elucidates the implementation of structural changes and presents a coherent approach for the practical application to the BDI(Baltic Dry-bulk Index), which serves as a representative maritime trade index in global market. The framework encompasses a range of F-statistics type methodologies for fitting, visualization, and evaluation of empirical fluctuation processes, including CUSUM, MOSUM, and estimates-based processes. Additionally, it provides functionality for the computation and evaluation of sequences of pruned exact linear time(hereafter PELT).

Key words: CUSUM, MOSUM, Strucutural Change

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Ⅰ. Introduction

The issue pertaining to the identification of structural changes in linear regression relationships has been a significant subject of investigation in the fields of statistics and econometrics. The primary categories of the tests for detecting structural change in data can be broadly classified into two groups: tests derived from the generalized fluctuation test framework Kuan and Hornik(1995) and tests relying on F-statistics Hansen(1992), Andrew and Ploberger(1994). The initial category include the CUSUM and MOSUM tests, as well as the fluctuation test. Conversely, the subsequent category encompasses the Chow and sup$F$-tests. There has been a growing focus on the structural change monitoring, particularly in relation to fields such as artificial intelligence(hereafter AI) and machine learning (hereafter ML). This involves commencing analysis after a historical phase characterized by the absence of structural changes, in order to examine new data and promptly identify any occurrence of structural change.

The theory supports a straightforward representative two methodologies for identifying and calculating various change-points. The proposed methodology consists of a two processes. In the first stage, a maximum of a MOSUM(moving sum) type statistic is utilized. This is followed by a second step, which involves a CUSUM(cumulative sum) refining step applied to an aggregated time series. Therefore, it is possible to identify the largest break occurring at several coordinates and also aggregate simultaneous breaks across multiple coordinates for a given time-point. By generalizing the high-dimensional Gaussian approximation theorem to incorporate dependent data with jumps, this theoretical framework enables the characterization of the asymptotic size and power of our multiple change-point test. Furthermore, it is possible to draw conclusions on the estimated breakpoints when the sizes of the breaks are modest. The theoretical framework we employ encompasses both weak temporal and strong or weak cross-sectional dependence, making it well-suited for heavy-tailed innovations. We offer a method for estimating a robust long-run covariance matrix, which may be of independent relevance. This study considers the utilization of our methods to demonstrate the practicality of identifying structure changes in the Baltic Dry-bulk Index (hereafter BDI).

This work focuses on the concepts and techniques for effectively implementing generalized fluctuation tests in a complete and adaptable manner, which accurately captures the shared characteristics to test multiple structure changes. Additionally, it provides options for presenting the outcomes in diverse formats. The concepts mentioned have been implemented and widely used for statistical computing, so called "Big Data" and "AI" back ground.

This study is structured as follows: Section 2 is going to provide a description of the typical linear regression model, which serves as the foundation for all subsequent tests. Additionally, the testing problem will be explicitly defined. Section 3 presents a dataset that is popularly included in the marine industry investigations and is utilized for the illustrative examples in this research article. The subsequent Section 4 provides illustrative instances for BDI and oil price with graphical representation along with the relevant limits, and the subsequent examination of structural changes through long-run relationship and residual of error correction processes. In Section 5 we presents concluding remarks.

II. Fundamental Frameworks to Detect Structure Breaks

The typical linear regression model should be taken into consideration.

$$y_t = x_t{'}\beta_t + u_t \tag{1}$$

where $t = 1, \ldots, T$ represents time index, y_t is the dependent variable, $x_t{'}$ is the transpose of the independent variable vector, β_t is the coefficient vector, and u_t is the error term.

At time t, the observation of the dependent variable, denoted as y_t, is determined by a set of independent variables $x_t{'}$. The error terms u_t are identically independently distributed(hereafter $i.i.d.$) with a mean of zero and variance of σ_t^2. The regression coefficients β_t are time-varying k -vector. Tests on structural change are focused on examining the null hypothesis that there is no presence of structural change. The null hypothesis, H_0 states that the coefficient β_t is equal to β_0 for all t ranging from 1 to T. In opposition to the notion of a time-varying coefficient vector, it is argued that different statistical tests may exhibit varying degrees of suitability, or power, when applied to different patterns of deviation from the null hypothesis.

It is postulated that the regressors exhibit non-stochastic behavior, with a norm of $\| x_t \| = O(1)$, and it is further assumed that the meaning or interpretation of the mathematical expression $\Sigma_{x'x}$. For a given finite regular matrix Q, the aforementioned constraints, which impose absolute regularity and exclude any trends present in the data, are assumed for the sake of simplicity. In certain cases, it is possible to apply these assumptions to dynamic models without altering the fundamental characteristics of the tests. However, since these specifications are not the primary subject of this study, they have been excluded from the discussion.

For efficient estimation, the Ordinary Least Squares(hereafter OLS) model is applied to the observations both prior to and following the probable change-point. At time t, given k regressors, the error sum of squares(ESS_t) is calculated using OLS residuals obtained from a segmented regression. Additionally, the residual sum of squares(RSS_t) is derived from the unsegmented model. For each conceivable change-point, a F -statistic is generated as follows,

$$F_{t_0} = \frac{RSS_t - ESS_t}{ESS_t/(T-2k)} = \frac{\hat{u}'\hat{u} - \hat{e}'\hat{e}}{\hat{e}'\hat{e}/(T-2k)} \tag{2}$$

where certain change point, t_0 is to the interval, $0 < t_1 \leq t_0 \leq t_2 < T$. Initially Chow(1960) was the first to provide a test for structural change in cases when the known change point t_0 is present. The test suggests two distinct regression models for the two subsamples categorized by t_0, and thereafter rejecting the null hypothesis wherever following test statistics is significantly large. The residuals $\hat{u}$ from the full model, $\hat{e}=(\hat{u}_A, \hat{u}_B)$ are the residuals from the restricted model where t_0 is certain change point to the interval. As an alternative and extended F-test to examine the validity of "no structural change" null hypothesis, one notable distinction specifies generalized fluctuation tests which is able to accommodate several patterns of structural changes. The alternatives can be defined based on following framework:

$$\beta_t = \begin{cases} \beta_A = (1 < t \leq t_o) \\ \beta_B = (t_o < t \leq T) \end{cases} \tag{3}$$

The Eq.(2) statistics assuming normality, F_{t_0}/k has an exact F-distribution with k and $T-k$ degrees of freedom, while F_{t_0} has an asymptotic χ^2 distribution with k degrees of freedom. However, the "Chow test" need change point in advance while the tests based on F-statistics do not need a specific change point. In particular, The monitoring process proposed by Chu et al.(1996) involves the computation of a recursive estimate upon the arrival of fresh data. This estimate is subsequently compared to β_t, which is an estimate derived from the historical sample. If the discrepancy between two values is significant, the null hypothesis is rejected and the monitoring procedure is terminated. Conversely, if the discrepancy is not deemed significant, the monitoring method is allowed to proceed.

In their seminal works, Anderew and Ploberger(1994) proposed three distinct test statistics, sup$F$, avg$F$, and exp$F$, which are derived from several types of F-statistics, including Wald, LM, or LR statistics.[1] These statistics are applicable to a broad range of models estimated using the generalized method of moments(GMM). The interpretation of these statistics is straightforward, and they exhibit desirable features when compared to alternative methods involving a single shift. The next two methods necessitate the calculation of partial sample estimates both prior to and subsequent to a hypothetical break point that is shifted across a section of the sample.

Ⅲ. Generalized Tests

The subsequent discussion pertains to the parameter β_t. The estimates of the coefficients, denoted as (t, j), is obtained using the OLS method. In what follows β_t, j is the OLS estimate of the regression coefficients based on the observations $t+1, \ldots, t+j$, and $\beta_t = \beta_0$ is the OLS estimate based on all observations up to t. Hence β_t is the common OLS estimate in the linear regression model. Similarly OLS residuals, $\widehat{u_t}$ are defined $\widehat{u_t} = y_t - x_t{}'\hat{\beta}$ with the variance $\widehat{\sigma^2}$ where X_t is the regressor matrix based on all observations up to t.

To capture the structural breaks in the series

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1) $\text{avg}F = \frac{1}{t_2 - t_1 + 1} \Sigma_{t=t_1}^{t_2} F_T(t)$,

$\sup F \rightarrow \sup F(t)$,

$\exp F \rightarrow_d \ln\left(\frac{1}{\pi_2 - \pi_1}\int_{\pi_1}^{\pi_2} \exp\left(\frac{1}{2}F(t)\right)dt\right)$

following recursive residuals are employed

$$\tilde{u_t} = \frac{y_t - x'_t \hat{\beta}_{t-1}}{\sqrt{1 + x'_t (X'_{t-1} X'_{t-1})^{-1} x_t}} \tag{4}$$

where $\tilde{\sigma^2} = \frac{1}{n-k} \Sigma_{t=k+1}^{n} (\tilde{u_t} - \bar{u_t})$ variance and zero mean. This estimation is based on the observations t. The significance of the variables $t+j$ and β_t in the context being equal to 0. The OLS estimate $(0, i)$ is derived from OLS method using all available data.

The generalized tests involve fitting a model to the provided data and generating an empirical process that captures the fluctuations observed in either the residuals or the estimates. The limiting process for the empirical process are well-established, where these boundaries determine the likelihood of crossing under the null hypothesis, denoted as α. If the empirical process interfere the boundaries, the magnitude of the fluctuation is improbably large, thereby leading to the rejection of the null hypothesis at a significance level α.

1. Fluctuation Tests

Zeileis(2005) presented a comprehensive perspective on the testing for structural change through the utilization of a generalized M-fluctuation test framework. The unified tests are constructed functional central limit theorem(hereafter FCLT) as its foundation, but employ distinct functionals for the calculation of test statistics. In order to evaluate the null hypothesis, the parameter β_t is estimated using M-estimation, which encompasses OLS, maximum likelihood estimation(ML), and various other robust estimation.

The expected value, $\Sigma_{t=1}^{T} \psi(y_t, x_t, \beta_t) = 0$ is assumed to be zero at time t under the null hypothesis. The parameter estimate, symbolized as β_t, is computed by utilizing the complete sample period, while incorporating a corresponding fluctuation mechanism to accommodate any deviations from stability. The estimates to the fluctuation process are contingent upon the selection of an appropriate estimating function $\psi(\bullet)$, which is expected to have a mean of zero at the true parameters. The utilization of de-correlated partial sums provides a method for capturing temporal structural changes in fluctuation. The resulting cumulative score process is commonly referred to as the empirical fluctuation process (hereinafter EFP).

$$\begin{aligned} EFP &= \hat{J} W_n(t, \hat{\theta}) \\ &= \hat{J} n^{-\frac{1}{2}}_{i=1} \Sigma_{t=1}^{T} \psi(y_t, x_t, \beta_t) \end{aligned} \tag{5}$$

where $\hat{J}$ is suitable consistent estimate of the covariance matrix of the scores $\psi(y_t, \beta_t)$ and $W_n(t) = \frac{1}{\tilde{\sigma}\sqrt{n}} \Sigma_{t=k+1}^{k+\lfloor Nt \rfloor} \tilde{u}_t$ under $(0 \le t \le 1)$. Brown(1975) proposed the consideration of cumulative sums of recursive residuals as a statistical approach. The process can be computed, cumulative sums of standardized residuals, where $N = T - k$ is the number of recursive residuals and $\lfloor Nt \rfloor$ represent the integer part of Nt. According to the null hypothesis, the empirical fluctuation process $W_n(t)$ converges to the Standard Brownian Motion (also known as the Wiener Process) $W(t)$ in the limiting process.

The subsequent functional central limit theorem(FCLT) is valid in $W_n(t) \Rightarrow W$.

In the presence of a single structural change point t_0, it can be observed that the recursive residuals will exhibit a mean, zero only until t_0 and afterwards deviate from its average value. Kramer(1988) demonstrate that the fundamental characteristics of the CUSUM statistic remain consistent even when subjected to less stringent assumptions, particularly in the context of dynamic models. Ploberger(1992) then proposed the utilization of cumulative sums of the OLS residuals as the foundation for conducting a structural change test. The empirical fluctuation process known as OLS-CUSUM is defined as follows:

$$W_n^0(t) = \frac{1}{\tilde{\sigma}\sqrt{n}} \sum_{i=1}^{\lfloor tn \rfloor} \tilde{u}_i \tag{6}$$

where $(0 \le t \le 1)$. In limiting process $W_n^0(t)$ is the standard Brownian bridge, $W_n^0(t) = W(t) - tW(0)$. The standard Brownian bridge, denoted as $W^0(t)$, can be described as the limiting process where $W_0(t)$ is equal to the product of $W(t)$ and $W(1)$. In the context of a singular structural shift alternative, it is expected that the trajectory will exhibit a maximum point in the vicinity of t_0.

The alternative approach for identifying structural changes involves examining shifting sums of residuals, as opposed to utilizing cumulative sums of the identical residuals. The resulting empirical fluctuation process does not include the cumulative sum of all residuals up to a specific time t. Instead, it comprises the sum of a predetermined number of residuals within a data window. The size of this window is specified by the bandwidth parameter h, which is a value between 0 and 1. The window is then shifted throughout the whole sample period. Therefore, the Recursive MOSUM process can be characterized by

$$M_n(t|h) = \frac{1}{\tilde{\sigma}\sqrt{n}} \sum_{i=k+\lfloor N_n t \rfloor+1}^{k+\lfloor N_n t \rfloor + \lfloor nh \rfloor} \tilde{u}_i \tag{7}$$

where $N_n t = (n - \lfloor N_n t \rfloor)/(1-h)$ and $(0 \le t \le 1-h)$. The expression $(0 \le t \le 1-h)$ represents a mathematical inequality with the variables t and h.

The OLS-based MOSUM process can be defined in a following way:

$$\begin{aligned} M_n^0(t|h) &= \frac{1}{\tilde{\sigma}\sqrt{n}} \sum_{i=\lfloor N_n t \rfloor+1}^{\lfloor N_n t \rfloor + \lfloor nh \rfloor} \tilde{u}_i \\ &= W_n^0\left(\frac{\lfloor N_n t \rfloor + \lfloor nh \rfloor}{n}\right) \\ &\quad - W_n^0\left(\frac{\lfloor N_n t \rfloor}{n}\right) \end{aligned} \tag{8}$$

where $(0 \le t \le 1-h)$.

The empirical MOSUM processes can be understood in terms of the limiting process, which corresponds to the increments of a Brownian motion. On the other hand, Eq.(8) suggests that the limiting process is characterized by the increments of a Brownian bridge. Chu et al.(1995) provides detailed exposition. If we assume a single structural change occurring at time t_0, it may be expected that both MOSUM routes will exhibit a shift around t_0 as well.

Describing fluctuation processes only based on residuals, it effectively provides unknown regression coefficients. The estimation of the $k \times 1$ -vector β_t follows a similar approach to the residual-based CUSUM and MOSUM-type procedures. It can be done recursively, where the number of observations increases over time, or using a moving data window with a fixed bandwidth h. The estimated β_t vector is then compared to the estimations obtained from the entire sample. The preceding concept gives rise to the fluctuation process, as described by Ploberger(1989), which is characterized by

$$Y_n(t) = \frac{\sqrt{i}}{\tilde{\sigma}\sqrt{n}}\left(\tilde{\beta}^{\lfloor nt \rfloor, \lfloor nh \rfloor} - \tilde{\beta}^{n}\right) \times \left(\left(X^{\lfloor nt \rfloor, \lfloor nh \rfloor}\right)'\left(X^{\lfloor nt \rfloor, \lfloor nh \rfloor}\right)\right)^{\frac{1}{2}} \quad (9)$$

The advantage of this approach is that the calculation only needs to be performed once. However, Kuan and Chen(1994) demonstrated that if there are dependencies among the regressors, rescaling can enhance the empirical size of the final test. The rescaled empirical fluctuation process exhibits a heuristic resemblance to its theoretical counterpart.

The type argument can be adjusted to accommodate any additional process type discussed in this section. The fitted process can thereafter be outputted, graphically represented, or subjected to the appropriate test for assessing structural change. In order to address the second concern, it is imperative to establish proper boundaries. The subsequent section will elucidate the concept of boundaries as they pertain to fluctuation processes.

The underlying principle shared by all generalized fluctuation tests is the rejection of the null hypothesis of "no structural change" when the empirical process the function exhibits an unusually significant fluctuation relative to the fluctuation of the limiting process. In the case of one-dimensional residual-based processes, the comparison is conducted using a suitable boundary $b(t)$, which the limiting process crosses with a specified probability α. Therefore, if the function intersects either $b(t)$ or $-b(t)$ at any given time t, it can be inferred that the fluctuation is highly unlikely to occur by chance. Consequently, the null hypothesis can be rejected with a confidence level of α. The methodology employed in k-dimensional estimates-based processes is comparable, with the exception that instead of establishing a boundary for the process itself, a boundary is established for absolute value for the function, where $\| \bullet \|$ represents a suitable functional that is applied to each component. The functionals 'max' and 'range' have been successfully implemented. The null hypothesis is deemed invalid if the magnitude of absolute value for the function exceeds a predetermined constant λ, which is contingent upon the chosen confidence level α, for all $i = 1, \ldots, k$.

The bounds for the MOSUM processes are constant values, denoted as $b(t) = \lambda$, which is a reasonable assumption given that the limiting processes exhibit stationarity. However, the circumstances surrounding the CUSUM procedures exhibit notable distinctions. Both the Brownian motion and the Brownian bridge, which are limiting processes, are non-stationary. Utilizing bounds that are proportionate to the standard deviation function of the related theoretical process appears to be a logical approach. The Recursive CUSUM and OLS-based CUSUM path are two methods that can be used to calculate the confidence level, with λ being the parameter that determines this level. However, the limits that are typically employed are linear in nature, as a closed-form solution for the crossing probability has been established. The conventional boundaries for the two processes are of a specific type. Zeileis(2002) examined the properties of the alternative boundaries show that the resulting OLS-based CUSUM test has better power for structural changes early and late in the sample period.

While the calculation and visualization of the empirical fluctuation process, along with its bounds, offer a comprehensive representation of the data, there may be instances where conducting a conventional significance test is still necessary. The task can be accomplished conveniently by utilizing the test statistics, which provides test statistic and the associated p-value.

2. multiple structure changes by PELT

Killick(2012) introduce a novel methodology for detecting change points that guarantees exactness. Estimtes for multiple change points are to minimize following cost function:

$$\sum_{i=1}^{m+1}\left[C\left(y_{(\tau_{i-1}+1;\tau_i)}\right)\right]+\beta f(m) \tag{10}$$

where a system has a number of change points, m, together with their positions, $\tau_{1:m}=(\tau_1,\ldots,\tau_m)$. The variable C denotes a cost function for a particular segment, whereas $\beta f(m)$ serves as a penalty term designed to mitigate the risk of over-fitting.

When considering the selection of a punishment, it is observed that the most prevalent choice in practice is a penalty that exhibits a linear relationship with the number of change points. In other words, the penalty function can be represented as $\beta f(m)=\beta m$. Examples of such penalties include Akaike's Information Criterion (AIC, Akaike(1974)) ($\beta=2p$) and Schwarz Information Criterion(SIC, also known as BIC; Schwarz(1978) ($\beta=p\log n$), where p is the number of additional parameters introduced by adding a change point.

In Eq.(10), cost function will be determined by minus the maximum log-likelihood:

$$C(y_{(t+1):s})=-\max\sum_{i=t+1}^{s}\log f(y_i|\theta) \tag{11}$$

where the parameter θ represents a segment, and the data within the segment follows an identically independently distributed($i.i.d.$) pattern with a density function denoted as $f(y_i|\theta)$.

Furthermore, we demonstrate that, under certain moderate constraints, the computational expense of our approach scales linearly with the quantity of data points. The present study proposes a methodology aimed at determining the minimum of cost functions, hence identifying the ideal number and position of change points. This method exhibits a computing cost that, given certain assumptions, is proportional to the number of observations. The PELT method, also known as

Pruned Exact Linear Time, incorporates a pruning step inside its dynamic programming algorithm. This step serves to decrease the computing burden without compromising the accuracy of the final segmentation. In simulations we compare PELT with both CUSUM and MOSUM Partitioning.

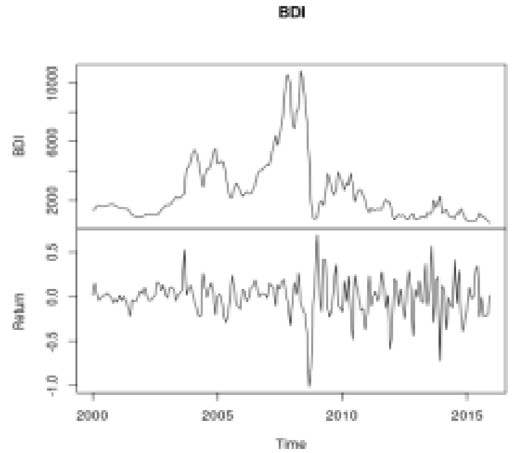
Ⅳ. Empirics

1. Data Description for Application to the Maritime Index

In the macroeconomic growth models, dynamic analysis focuses on the long-term trend of economic growth. It is essential to discuss endogenous and exogeneous factors of technology in the economy that is able to cause abrupt fluctuations of upward or downward to the mean and trend. Hence, it is crucial to analyze long-term fluctuations based on the characteristics of economic fluctuation, taking into account exogenous shocks and endogenous factors. It is crucial for us to analyze and model recent global recession which is able to predict when the situation is due for an upturn.

Along the same line, in case of fluctuations in the maritime industry, freight rates indicated by indices reflect both external and internal factors that cause sudden fluctuations. Initially, Kim and Chang(2013) examine the relationship between fluctuations in the shipping economy and shifts in market demand and find that fluctuations in the shipping economy can be both cause and consequence of changes in market demand. Furthermore, the study highlights the impact of the shipping economy recession that transpired prior to and following the 2008 financial crisis on the partial equilibrium of the overall economy. The process of repeating the rise and fall is a representative example of rapid economic fluctuations caused by exogenous economic shocks.

Figure 1. Level and Return for the BDI During 2000-2016



In order to examine fluctuations around 2008 crisis, Figure.1 shows the Baltic dry bulk freight rate index(hereafter BDI) and rate of return of it. Examining the series located at the upper section, it is evident that an initial level of 1000 in January 1985, predominantly remains below 3000, with the exception of the periods from 2003 to 2010. In particular, before the 2008 global financial crisis, it showed a rapid rise reaching a level of about 12,000. These dynamic characteristics over time appear differently depending on the period. In other words, when looking at the period before 2003, from 2003 to 2008, and after 2010, there is no trend increase in the shipping industry except for the period from 2003 to 2010. Hence, it is plausible to suggest that employing a linear model for analysis, which incorporates a specific linear trend either from an exogenous business cycle model or a predetermined trend, may mislead.

Kim and Chang(2013) to the rapid changes in the shipping industry around 2008 reflects the characteristics of each period, taking into account the characteristics of the global financial crisis rather than targeting the overall period.

Table 1. Test for F–statistics, CUSUM, MOSUM and ME

	F-statistics			CUSUM		MOSUM		ME	
	Statistics	p-value		Statistics	p-value	Statistics	p-value	Statistics	p-value
sup$F$	29.91	0.0000	OLS	1.29	0.0691	1.27	0.0282	2.01	0.01
avg$F$	11.09	0.0011	Rec	0.46	0.7000	0.95	0.3072		
exp$F$	11.86	0.0002							

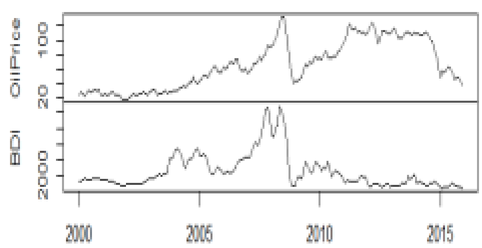
Recent approaches for big data and artificial intelligence focuses on first classifying the dynamic characteristics of the data. Therefore, to consider the characteristics of economic fluctuations shown in the data first we analyze data segment and discuss economic shock caused by exogenous shocks.

2. Empirical Fluctuation Processes with Bivariate System

We investigate the evidence of structural changes in bivariate system during the periods from 2000 to 2016. The series for level and retrun are shown in Figure 1. There are sudden up and down turns between 2003 and 2008. Kim and Chang(2020) estimated multiple structural changes during the peoriod with very high posterior probabilities.

Since the freight risk shows a discontinuity while experiencing two rapid economic fluctuations, In this investigation we employ bivariate investigation including BDI and Oil Price. We apply empirical fluctuation processes to the residual of error correction model because of nonstationarity to the variables. The relationship between nonstationary series therefore depends on the stability of the residuals. In particular, the rapid changes around 2008 seriously damage the stability of the data, making predictions more difficult.

Figure 2. Oil Price and BDI during 2000–2016

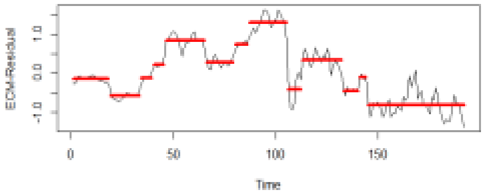


Due to its discontinuity caused by several times rapid economic swings, verification of the fluctuation is challenging based on simple analysis methods. This study employs a bivariate approach, specifically examining the relationship between BDI and oil prices that is directly able to affect freight rate. The empirical fluctuation processes are utilised to analyse the residuals of an error correction model(hereafter ECM) and the strucural breaks in residuals of ECM are summarized in Table(1). All the tests reject the null hypothesis with the significance level $\alpha = 0.01$ except both CUSUM and Recursive MOSUM tests. To check model stability several previous investigation have employed CUMSUM types of tests but this empirical results give a hint for the location of change-point. We, therefore, the change-point estimators can be made based on the change test for parameter change models.

3. Application to PELT

As an additional analysis, we apply the regression fit and distribution in order to understand the disparity between the estimated findings obtained from the complete estimation period of the data and the subsample commonly utilized in various research. In this section, we provide the findings of PELT estimate, which is employed by Kim and Chang(2020), to examine potential changes in the mean, variance, or both mean and variance in the BDI that represents the shipping industry to the extended periods. As shown in Kim and Chang(2020), Figure(3) presents the results of applying PELT to the average of the weekly BDI. The estimate presents three transition points those are very similar to the results provided by Kim and Chang(2020) for PELT.

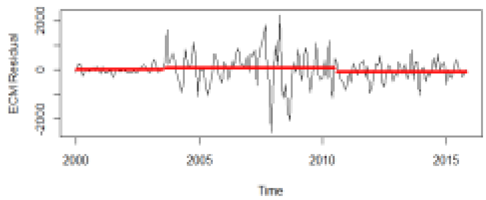
Figure 3. PELT for BDI



We are going to specifically pay more attention to the weekly dataset during 2000-2016 and test residual for the two-stage estimates suggested by Engle and Granger(1987), which represnts long-run relationship. As shown in Figure(3), there are 12 change-points that implies structural breaks. This is one of the primary factors contributing to the lack of statistical significance in estimates using linear form based analysis.

To the above issue Castle(2010) suggest co-integration-based equilibrium-correction model(EqCM) those face forecasting problems. They consider alleviating such forecast failure by updating, intercept corrections, differencing, and estimating the future progress of an 'internal' break.

Figure 4. PELT for Residual from BDI and Oil Price



However updating leads to a loss of cointegration when an EqCM suffers an equilibrium-mean shift, but helps when collinearities are changed by an 'external' break with the EqCM staying constant. Figure(4) presents the residual for the full error-correction model and still shows 2 change-points to the same period.

Ⅴ. Concluding Remarks

As increasingly longer data sets are being collected, more and more applications require the detection of changes in the distributional properties of such data. For example, in macroeconimics and finance, interest lies in detecting changes in the volatility of time series. Typically such series will contain several changepoints and there is a growing need to be able to search for changes efficiently. It

is this search problem which we consider in this paper for structural change in the mean and variance. Our proposed test based on F-statistics is generally applicable to detect changes in regression models. No version of the structural change tests considered is superior to the F-statistics. The CUSUM and MOSUM tests are considered and compared with the proposed test.

Furthermore, we conduct a test using the PELT approach to examine the turbulent period from 2000 to 2016. This test encompassed both the analysis of the long-run connection and the examination of the residual of the error correction model. Both adjustments provide improvements as compared to keeping an estimated model before to the break. However, it is possible that an estimated model of the break process may yield even better performance. Additional investigation is anticipated to be conducted utilising a modified experimental procedure to assess various alterations and enhance the accuracy of estimations. Further investigation can be conducted on the tests and estimators pertaining to linear structural change and time series structural change.

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해상운임의 구조변화 리스크 추정

김현석

국문요약

본 연구는 기존의 비선형 추정에 기초한 구조 단절/변화를 검정하기 위한 모형을 선형 회귀 분석으로 일반화한 모형으로 효율적 추정이 가능함을 제시하고자 한다. 특히, 효율적인 추정을 위해 인공지능, 머신러닝 등 분야와 관련해 구조 단절/변화 모니터링에 대한 관심이 높아지는 최근 이슈에 대해 선형 회귀에 근거한 본 연구의 실증분석 결과는 구조 단절을 명확하게 추정하였으며, 글로벌 시황을 나타내는 대표적인 건화물선 운임 지수(발틱 드라이 벌크 지수, BDI)에 대한 적용 결과는 기존 연구와 일치하는 추정 결과를 제시한다. 이상의 선형 회귀에 근거한 분석은 CUSUM, MOSUM, F-통계 기반 프로세스 등 경험적 변동 프로세스의 피팅, 시각화 및 평가를 위한 다양한 유형의 추정에서 통계적으로 유의한 것으로 나타났다. 추가적으로 기존 연구에서 제시한 PELT(pruned exact linear time)를 적용한 추정에서도 유사한 추정 결과를 각각 나타낸다.

주제어: CUSUM, MOSUM, 구조변화