Pamukkale Üniversitesi

Sosyal Bilimler Enstitüsü Dergisi

Pamukkale University Journal of Social Sciences Institute

ISSN1308-2922 EISSN2147-6985

Article Info/Makale Bilgisi

√Received/Geliş: 26.03.2018 √Accepted/Kabul: 08.08.2018

DOİ: 10.30794/pausbed.409482

Araştırma Makalesi/ Research Article

Türker Bayrak,Ö., Aytaçoğlu, B., Yüksel Haliloğlu, E., (2019). "Linear Profile Monitoring Adapted to Construct Early Warning System in Economics: A Pilot Study From Energy Sector" , *Pamukkale Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, sayı 34, Denizli, s. 47-55

# LINEAR PROFILE MONITORING ADAPTED TO CONSTRUCT EARLY WARNING SYSTEM IN ECONOMICS: A PILOT STUDY FROM ENERGY SECTOR*

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**Abstract**

In this study, control charts for monitoring linear profiles are adopted to early warning system (EWS) to see if global crises can be detected before they occur so that preventive actions can be taken by the policy makers. For this purpose, the relation between the annual gross domestic product (GDP) and energy consumption of G8 and big emerging countries through the years 1980-2012 is observed. Phase I analysis indicated that the model parameters are autocorrelated through time. Thus, the Shewhart and EWMA charts for linear profile monitoring are adopted to take this into account and found that EWMA is better. It is seen that the 2008 global crisis can be detected whereas relatively local Asian crisis cannot. This is the first study that integrates linear profile monitoring schemes to EWS and that takes into account the correlation among profiles with different explanatory variables (x-values) for each profile.

**Keywords:** *Crisis, Energy, Linear Profiles, Monitoring, Control Chart.*

# DOĞRUSAL PROFİLLERE DAYALI KONTROL ŞEMALARININ EKONOMİDE ERKEN UYARI SİSTEMİ OLUŞTURMAK İÇİN UYARLANMASI: ENERJİ SEKTÖRÜNDE BİR PİLOT ÇALIŞMA

**Özet**

Bu çalışmada, küresel krizleri öngörebilmek ve dolayısıyla karar alıcılar tarafından önleyici aksiyonlar alınabilmesi amacıyla erken uyarı sistemi oluşturmak üzere doğrusal profil için kontrol şemaları adapte edilmiştir. Bu doğrultuda, gayri safi yurt içi hasıla (GSYH) ile G8 ve gelişmekte olan büyük ülkelerin 1980-2012 yıllarındaki enerji tüketimi arasındaki ilişki incelenmiştir. Faz I analizi model parametrelerinin zaman içinde otokorelasyon içerdiğini göstermiştir. Dolayısıyla, bu otokorelasyonu dikkate alan, doğrusal profiller için Shewhart ve EWMA şemaları kullanılmış ve EWMA şemasının daha iyi olduğu tespit edilmiştir. 2008 küresel krizinin tespit edilebildiği ancak yerel Asya krizinin tespit edilemediği görülmüştür. Bu çalışma, hem doğrusal profillerin izlenmesi için geliştirilen kontrol şemalarını erken uyarı sistemi oluşturmak amacıyla kullanan hem de açıklayıcı değişkenlerin (x-değerleri) profilden profile çeşitlilik arz etmesi ile profiller arası korelasyonu da dikkate alan ilk çalışmadır.

**Anahtar Kelimeler:** *Kriz, Enerji, Doğrusal Profil, İzleme, Kontrol Şeması.*

* An early version of this work was presented in 9th International Statistics Day Symposium, 10-14 May 2014, Antalya, Turkey and in a seminar at Middle East Technical University, 22 May 2014.

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## 1. INTRODUCTION

Both local and global crises are unfortunately so common in history. Crises can be broadly classified as financial and economic. Financial crises are related with banking sector, currency and capital markets whereas economic crises are related with macro economic conditions like fall in GDP, current account deficits, unemployment etc. that can take the form of a recession or a depression. Financial crises affect the macro economic conditions and turn into economic crises if they are not addressed properly and preventive actions are not taken. Therefore, attempts to identify a way to forecast an incoming crisis began so that corrective actions could be taken to prevent it or at least to degrade its effects.

For this purpose, beginning with the 90s, Early Warning Systems (EWS) models trying to determine the factors leading the financial crisis are started to be developed by the international organizations like International Money Found (IMF). So far, many methods are developed starting from finding leading indicators followed by signal approach, probit approach and many more techniques like artificial neural networks. Almost all of these models try to identify the causes of the crises and based on these factors and their effects, try to figure out an incoming crisis. However, since the structure of each crisis is unique, a method that can foresee a type of crisis might not well predict another type of crisis.

Thus, in this study, a methodology is tried to be developed not based on a cause of a crisis but rather investigating a change in the affected macro economic relations. Since a crisis cause a loss in GDP whose main contributor is the consumption, the relation between GDP and energy consumption is investigated to see whether the coming crises could be foreseen. For this purpose, newly developing quality control schemes for profile monitoring are adopted. Application of a newly developed quality control technique to a macroeconomic problem is the first to the authors' knowledge. Therefore, this study is not only different from the literature by looking from the consequences side rather than causes side to a crisis but also unique by adopting a new developing quality control scheme. Besides, since the existing schemes in profile monitoring are not suitable for the structure of the data used in the analysis, their assumptions are relaxed and the schemes are adopted according to these relaxed assumptions. A brief discussion of the methods in literature for both EWS and profile monitoring, and how this study differs from them are discussed in Section 2 while the adopted methodology is given in Section 3. The results and discussion of the analysis can be found in Section 4; and finally Section 5 provides the conclusion including the future study.

## 2. LITERATURE REVIEW

Although the researchers and policy makers are interested in constructing EWS for crises for many years, the recent big global crisis of 2008-09 renewed this interest and its importance so that it is asked from the IMF 'to provide early warning of macroeconomic and financial risks and the actions needed to address them' by the April 2009 London summit. First attempts for crises analysis were held out in terms of finding out leading indicators (Bilson, 1979) and constructing theoretical models to explain them (Krugman, 1979). Then the EWS idea based on signals approach is proposed by Kaminsky et al. (1998) where the focus is on currency crises. In this methodology, an indicator warns about a coming crisis if it exceeds a certain threshold. As an alternative, Berg and Pattillo (1999) suggest probit based models where the dependent variable is a binary zero-one variable referring whether there is a crisis ahead or not yielding the crisis probability at different points in time which made discrete choice models popular in this area. In recent years, there are many other methods employed to construct EWS like use of binary recursive trees, artificial neural networks and genetic algorithms, Markov switching models and panel data approaches. For review of literature one can refer to Kaminsky et al. (1998), Abiad (2003), Hawkins and Klau (2000) and Frankel and Saravelos (2012).

Besides the methodology they use, developed EWS differ according to their crises definition indicating that there is no consensus in the literature on how to define crisis. Some define it in terms of nominal variables like large currency depreciations (Frankel and Rose, 1996; Kaminsky and Reinhart, 1999), while others define in terms of stock market crashes (Grammatikos and Vermeulen, 2010), or rapid decreases in asset prices (Alessi and Detken, 2011). Alternatively, there are studies defining it in terms of its real costs like loss of GDP or loss of wealth (Caprio and Klingebiel, 2003; Laeven and Valencia, 2008). In this study, we follow this last definition and consider the crisis as a loss of GDP since, whatever the definition of crisis is, it will cause a loss of GDP eventually. Hence, the global crises are tried to be detected based on the changes in relations between macroeconomic variables; namely GDP and energy consumption.

As it is stated in Lee (2006), the causal relationship between energy consumption and economic growth can be various. Simply, rising energy consumption increases the production level as well as the consumption level in a country, which results in increase in income. If causality runs from energy consumption to economic growth, it means that economy is energy-dependent and energy is a stimulus for economic growth. A decrease in energy consumption might potentially indicate a fall in income therefore; macroeconomic energy policies should be designed accordingly. On the other hand, if causality is from economic growth to energy consumption, it indicates that economy is less energy-dependent (there are other major factors driving the economic growth) and macroeconomic policies favoring energy conservation might not have so much negative impact on economic growth, contrary to other way of causality. Finally, no causality between energy consumption and economic growth indicates that increase in energy consumption or implementation of energy conservation policies are expected to neither boost the economic growth nor shrink the income. Therefore, it is important to examine the casual relation between energy consumption and income, especially in crisis periods to design appropriate macroeconomic policies without worsening economic growth.

There are various studies analyzing this relationship for different countries and periods with different variables and techniques. The well-known initiating study in this area belongs to Kraft and Kraft (1978) reporting uni-directional causality from GNP to energy consumption for the U.S. during 1947-1974. Later studies for the U.S. concluded both supporting and contradicting results for different time periods. When emerging and developed countries are considered, it is found that some have uni-directional causality from energy consumption to GDP; while others have bi-directional, neutral, or uni-directional causality from GDP to energy consumption. As can be seen, the conclusions regarding this relation are quite ambiguous. Comprehensive summary tables outlining the features of the energy consumption-economic growth relationship can be found in Lee (2005; 2006) and Huang et al. (2008). Hence, in this study, we take causality from energy to GDP since energy is a good indicator of consumption which is the main component of GDP.

The analysis requires observing cross sectional data over time, named as longitudinal or panel data. The previous studies use panel data mainly for increasing the number of useful observations to gain accuracy in estimation (Berg et al., 2008) for all types of approaches to the problem mentioned above. However, we both differ from them in terms of methodology and the way of handling panel data. We first establish the relation between macroeconomic variables by linear regression method at each point in time separately; i.e. cross-sectional modeling. Then, to observe the behavior over time for early warning global crisis, we introduce linear profile control charts, a tool newly being developed in statistical process control (SPC).

The basic idea behind SPC is to spot a change in the process before producing a low qualified product. For this purpose, a control chart which is a graph having upper and lower limits is constructed through time. A control chart has two analysis phases. In Phase I, the aim is to evaluate the process stability and estimate the parameters for control charts by the use of historical data. Thus, the limits used in the charts are determined in this phase. The aim of Phase II analysis is to detect the shifts in process parameters as soon as possible. The current datum is compared with the determined limits for this purpose. Being within the limits is an indication of in control process. Else, the process is said to be out of control meaning it is affected by special causes of variation and an action has to be taken to return the process in control again.

So far, the control charts were related to a univariate or vector of multivariate quality characteristics. However, in some cases, the quality of a product or process can be defined as a relation between two or more variables that can be linear, nonlinear or polynomial. This relation is named as profile. The idea is mostly motivated by calibration applications (Mestek et al., 1994; Stover and Brill, 1998; Kang and Albin, 2000) where mainly the relation is linear. There are different methods developed to monitor simple linear profiles in literature for both Phases I and II. For Phase I, Mestek et al. (1994), Stover and Brill (1998) and Kang and Albin (2000) recommend $T^2$ type of control charts where a single control chart is produced for all parameters. Kim et al. (2003) recommend coding the explanatory variable so that the average becomes zero yielding the parameters become independent, and then constructing individual Shewhart-Type control charts for each one.

Phase II approaches are divided into two as (i) omnibus control charts for monitoring simultaneously the intercept and slope and (ii) individual control charts for monitoring them separately. $T^2$ and Exponentially Moving Average (EWMA) approach (Kang and Albin, 2000), Multivariate Cumulative Sum (MCUSUM) approach (Noorossana et al., 2004) are among the omnibus charts whereas EWMA chart approach of Kim et al. (2004) and Cumulative Sum (CUSUM) chart approach of Saghaei et al. (2009) are the ones for the individual control charts. Since detecting the source parameter of an out-of-control point in the omnibus charts is hard to figure out, individual charts are better for interpretation. For the other methods proposed to monitor linear profiles as well as more complicated models like polynomial and nonlinear profiles, and for further discussions and details, one can refer to Noorossana et al. (2011).

Known to the knowledge of authors, this is the first study that profile control charts are used to construct EWS in economics. For this, energy sector, which is highly encouraging area for governments and global policy makers, is selected as a pilot application and tried to figure out whether global crises defined as loss in GDP can be detected before it occurs so that preventive actions could be taken. Besides the contribution of EWS in economics, the study contributes to the linear profile monitoring literature in two ways: (1) relaxing the assumption of same fixed X-values through all profiles which is unrealistic in our case (2) extending the methodology to the case where the profiles at different times are correlated. Although different methods considering autocorrelation within profiles are suggested in literature, there is only one study dealing with between profile correlations done by Noorossana et al. (2008). It assumes that the error term follows autoregressive model of order one (AR(1)) and again same fixed X-values are assumed for each profile. Besides, the recommended methodology is for Phase II only; i.e. it assumes all the parameters known. Therefore, it is not suitable for our practice.

**3. MATERIAL AND THE METHODOLOGY**

In this study, big emerging countries except Poland; i.e. Brazil, China, Egypt, India, Indonesia, Mexico, Philippines, South Africa, South Korea and Turkey, and G8 developed countries except Russia are considered. The exclusion of Russia and Poland is due to the lack of full data among the studied years 1980-2012. 1980-1994 are taken as Phase I years to estimate the parameters of control charts and the remaining years are taken as Phase II to see if the chart can detect the global 2008 crisis or 1997 Asian crisis. Although there were crises in Southern Cone of Latin America (1981-1982); Latin America (1982-1989); Western Europe (1992-1993) and Mexico (1994-1995) during Phase I period, it is thought that they will not affect the estimation procedure since they were more local crises. Actually when the stability of Phase I analysis is controlled, this belief is seen to be correct since there were no out-of-control points in those years. The annual data of GDP at current prices in $ and primary energy consumption in quadrillion Btu is gathered from Data stream and International Energy Agency web-based data delivery system.

**3.1. Phase I Methodology**

Suppose for a sample j of size n collected over time, we have ($x_{ij}$ ,$y_{ij}$) as observations. Thus, the first subscript i denotes observation whereas j denotes the profile collected over time. Further, suppose that a simple linear regression model (can also be log-linear or double log-linear model) is adequate to model the data so that the model for the in control process is:

$$\mathrm{Y_{ij}} = \mathrm{A_0} + \mathrm{A_1 X_{ij}} + \eta_{\mathrm{ij}}\ , \quad i = 1, 2, \ldots, n\ ; \ j = 1, 2, \ldots, m, \tag{1}$$

where $A_0$ and $A_1$ are the model parameters and $\eta_{ij}$ are independent and normally distributed random variable with mean 0 and variance $\sigma_\eta^2$. As recommended by Kim et al. (2003), explanatory variable, $X$, is coded by subtracting its mean to make the estimates of slope and intercept parameters independent so that separate control charts can be constructed for signaling. Thus, the model in Equation (1) transforms to

$$\mathrm{Y'_{ij}} = \mathrm{B_0} + \mathrm{B_1 X'_{ij}} + \eta_{\mathrm{ij}}\ , \quad i = 1, 2, \ldots, n\ ; \ j = 1, 2, \ldots, m, \tag{2}$$

where $B_0 = A_0 + A_1\overline{X_j}$, $B_1 = A_1$ ,$Y'_{ij} = Y_{ij}$, $X'_{ij} = (X_{ij} - \overline{X_j})$, and $\overline{X_j} = \sum_{i=1}^{n} X_{ij}/n$. The least squares estimators of $B_0$ and $B_1$ for the j<sup>th</sup> profile are $\widehat{B_0} = \overline{y'_j}$ and $\widehat{B_1} = S_{x_j y_j}/S_{x_j x_j}$, respectively. They are both normally distributed with means $B_0$ and $B_1$, variances $\sigma_\eta^2/n$ and $\sigma_\eta^2/S_{x_j x_j}$, respectively, and the covariance between them is zero. Thus, univariate control charts for each parameter, $B_0$, $B_1$ and $\sigma_\eta^2$, can be constructed separately if there is no correlation between profiles. However, in our study, due to the time series nature of the variables, there appeared correlation among the profiles making such univariate control charts inapplicable. To overcome this problem, appropriate ARIMA(p,d,q) models are fitted to each parameter given as

$$\phi(\mathrm{B})(1-\mathrm{B})^{\mathrm{d}}\mathrm{W_t} = \theta(\mathrm{B})\varepsilon_{\mathrm{t}} \tag{3}$$

where B is the backward shift operator defined as $\mathrm{B^k} W_t = W_{t-k}$, $\phi(\mathrm{B})$ and $\theta(\mathrm{B})$ are polynomials of degree p and q; respectively, d is a nonnegative integer and $\varepsilon_j$ is independent and normally distributed random variable with mean 0 and constant variance $\sigma$. Hence, univariate control charts can now be applied to the residuals of the fitted models given in Equation (3); separately. We propose two control charts for each parameter: (i) The classical Shewhart control chart with the upper and lower limits

$$\mathrm{UCL} = \hat{\mu} + 3\hat{\sigma}, \text{ and } \mathrm{LCL} = \hat{\mu} - 3\hat{\sigma}; \text{ respectively,} \tag{4}$$

where $\hat{\mu}$ and $\hat{\sigma}$ are the mean and MSE of the residual of the corresponding fitted model given in Equation (3) and (ii) EWMA control chart where the EWMA statistic is the weighted average of the j<sup>th</sup> residual of Equation (3) denoted by $e_j$ and the previous residual given as

$$\mathrm{Z_j} = \lambda \mathrm{e_j} + (1-\lambda)\mathrm{Z_{j-1}}, \quad 0 < \lambda < 1 \tag{5}$$

where $\lambda$ is the weighting constant and $Z_0 = \hat{\mu}$. The upper limit, central line and lower control limit are

$$\mathrm{UCL} = \hat{\mu} + L\hat{\sigma}\sqrt{\frac{\lambda}{(2-\lambda)}[1-(1-\lambda)^{2t}]}$$
$$\mathrm{CL} = \hat{\mu} \qquad (6)$$
$$\mathrm{LCL} = \hat{\mu} - L\hat{\sigma}\sqrt{\frac{\lambda}{(2-\lambda)}[1-(1-\lambda)^{2t}]};$$

respectively, where *L* is the multiple of the sample statistic standard deviation that determines the false alarm rate. *L* and $\lambda$ are determined according to a specified ARL given by Lucas and Saccucci (1990).

These estimates of parameters in Equations (2-6) can be used for future monitoring if they are obtained from a stable process. Hence, when the control charts are constructed there has to be no out-of-control points. If there exists, each out-of-control point is examined for an assignable cause. If it is found, the out-of-control point is discarded and the control limits are recalculated. However, since the profiles are correlated, this omission will destroy the time series structure of the data. To avoid this, imputation techniques used in time series can be employed. This procedure has to be repeated till there are no out-of-control points in Phase I data.

### 3.2. Phase II Methodology

Once the parameters are determined in Phase I analysis, these values can be used in Phase II analysis for future monitoring of out-of-control points, if exists. Hence, the procedure will be as follows: First we will fit the regression line given in Equation (2) for the new profile. Then, obtain the residual value from the Equation (3) for each parameter where the model parameters in Equation (3) are the values obtained during the model identification in Phase I analysis. Finally plot this residual value to the corresponding control chart where the limits are determined in Phase I. Repeat this procedure for the incoming profiles in Phase II stage.

## 4. RESULTS AND DISCUSSION

The regression model given in Equation (2) is estimated for each year between 1980 and 1994 in Phase I analysis. Here the dependent variable, $\mathbf{Y}'_{\mathbf{ij}}$ **,** is ln(*GDP<sub>ij</sub>*); i.e. natural logarithm of the i$^{th}$ country's GDP at j$^{th}$ year, and the explanatory variable, $\mathbf{X}'_{\mathbf{ij}}$, is coded values of the natural logarithm of the i$^{th}$ country's energy consumption at j$^{th}$ year, The results obtained can be seen in Table 1.

**Table 1: The Estimates of the Parameters in Phase I Analysis.**

| Year | $B_0$ | $B_1$ | $\sigma_\eta^2$ | Year | $B_0$ | $B_1$ | $\sigma_\eta^2$ | Year | $B_0$ | $B_1$ | $\sigma_\eta^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1980** | 26,094 | 0,933 | 0,304 | **1985** | 26,183 | 0,999 | 0,248 | **1990** | 26,760 | 1,073 | 0,456 |
| **1981** | 26,141 | 0,926 | 0,303 | **1986** | 26,297 | 1,050 | 0,358 | **1991** | 26,789 | 1,088 | 0,495 |
| **1982** | 26,122 | 0,942 | 0,295 | **1987** | 26,428 | 1,060 | 0,421 | **1992** | 26,864 | 1,075 | 0,513 |
| **1983** | 26,117 | 0,977 | 0,262 | **1988** | 26,549 | 1,071 | 0,444 | **1993** | 26,905 | 1,059 | 0,484 |
| **1984** | 26,142 | 0,982 | 0,238 | **1989** | 26,644 | 1,064 | 0,395 | **1994** | 26,982 | 1,078 | 0,494 |

When the time series plots, autocorrelation and partial autocorrelation functions of each parameter are drawn, it is found that the slopes follow a Random Walk, whereas intercepts and error variances follow ARIMA(1,1,0) and AR(1) models; respectively. The fitted models are as follows:

$$\hat{B}_{1j} = B_{1(j-1)}\ , \qquad (7)$$
$$\widehat{\nabla B}_{0j} = 0.02587 + 0.591\nabla B_{0(j-1)},\ \text{and} \qquad (8)$$
$$\hat{\sigma}_j^2 = 0.01447 + 0.9636\sigma_{j-1}^2;\ \text{respectively,} \qquad (9)$$

where $\nabla$ is the difference operator. The residuals of each ARIMA model fitted are checked for normality, independence and homoscedasticity and found that there is no assumption violation. Thus, the Shewhart and EWMA charts given by the Equations (3-6) are constructed for each residual obtained from the ARIMA models given in Equations (7-9). To construct the EWMA chart $\lambda$ and L are taken to be 0.15 and 2.8; respectively, to obtain approximately in-control ARL of 370 according to Lucas and Saccucci (1990).

The Shewhart and EWMA chart for the residuals of slopes' model given in Equation (7) can be found in Figure 1. As can be seen from the Phase I part of Figure 1, all the points are in-control meaning that the set control chart can be used for Phase II analysis for both methods. The corresponding charts for the residuals of intercepts' model given in Equation (8), and for the residuals of variances' model given in Equation (9) can be seen in Figure 2 and 3; respectively. Similar results can be derived from the Phase I part of each graph indicating that the process is stable and the charts constructed can be used for future monitoring of out-of-control points, if exists.

When the Phase II part of Figure 1 covering years 1995-2012 is considered, it can be seen that EWMA chart for monitoring slope changes gives an alert at 2005, three years before the 2008 global crisis whereas Shewhart chart indicates no point outside the limits. However, there is an anomaly after 2002 in Shewhart chart that all the points are below the central line which is unexpected.

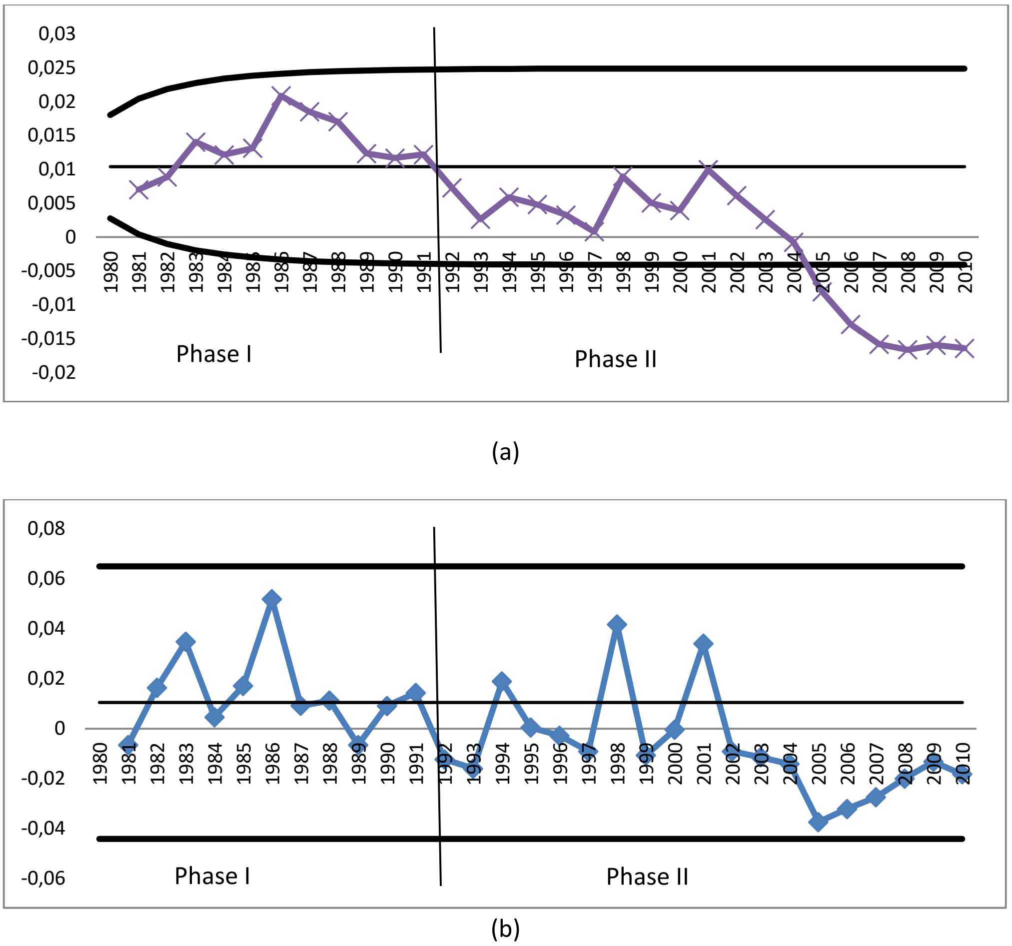
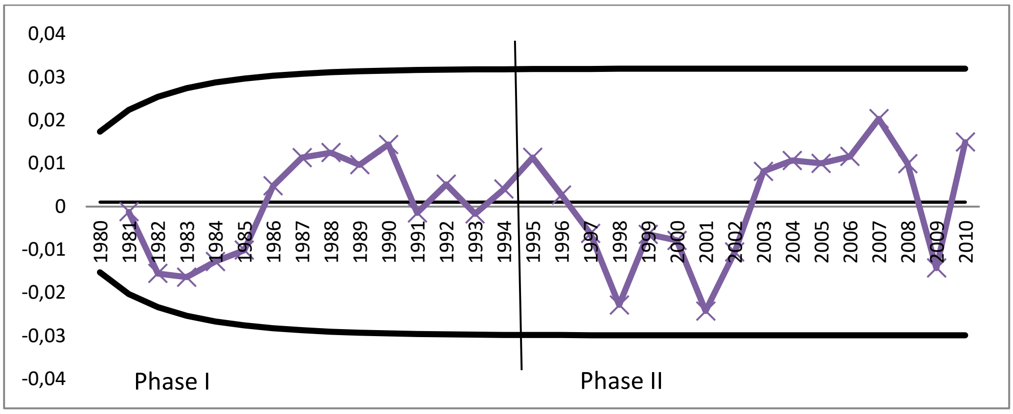
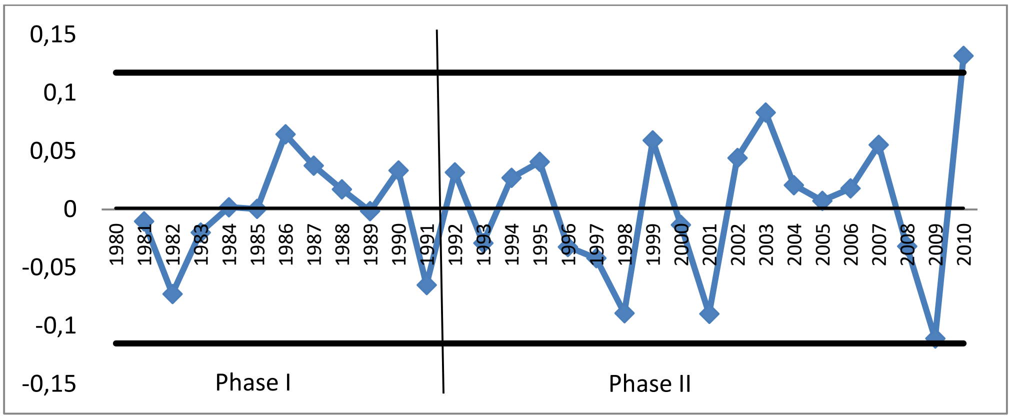



**Figure 1: (a) EWMA Control Chart and (b) Shewhart Control Chart for the Residuals of the Slopes' Fitted Model**

From the Phase II part of Figure 2, it can be seen that although EWMA chart for monitoring intercept changes does not yield an out-of-control point, Shewhart chart gives a signal at 2010 with a high but in-control value for 2009. Having in-boundary changes for intercept indicates that there are not significant changes in the level values of energy consumption and GDP. Combined with the implications of Figure 1, level changes for the variables are not significant; however, trend changes are suggesting a break point after 2005. This implies altered nature of the relationship between energy consumption and GDP.




(a)

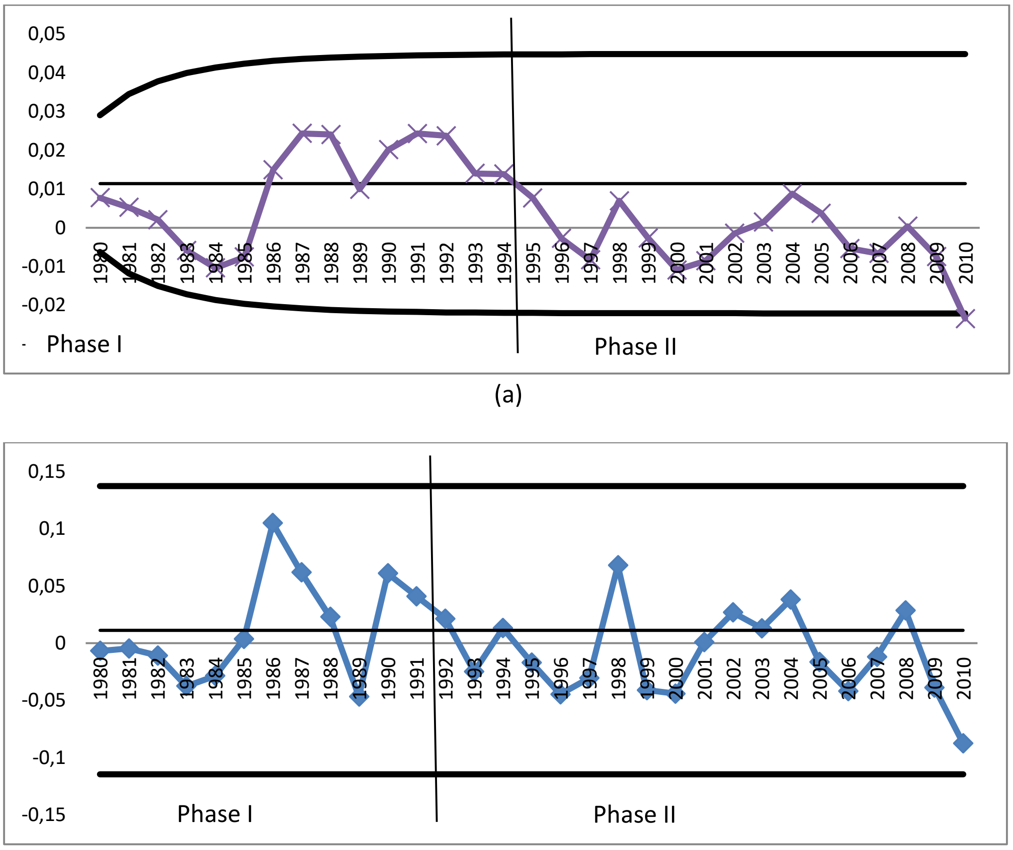



(b)

**Figure 2: (a) EWMA Control Chart and (b) Shewhart Control Chart for the Residuals of Intercepts' Fitted Model.**

When we consider the variance changes, we see from the Phase II part of Figure 3 that, it is in-control for both charts. However, the structure of EWMA chart is doubtful in the sense that all values of Phase II are below the central line. This is the indication of change in the model of Equation (2) which supports the alert obtained from the control chart for the residuals of the slopes' in Figure 1. Besides, it is the sign of increased volatility, which can be considered as instability in the energy consumption-GDP relationship.

The observed alterations in the energy consumption-GDP relationship indicate (i) changes in the behavior of people (both in terms of individual and industrial utilization) towards energy consumption and (ii) changes in income dependent on energy consumption. When these changes go beyond control limits, this can be accepted as significant variation in energy consumption-GDP link, which should be investigated carefully and macroeconomic energy conservation policies should be designed accordingly.




(b)

**Figure 3: (a) EWMA Control Chart and (b) Shewhart Control Chart for the Residuals of Variances' Fitted Model.**

## 5. CONCLUSION

In this study, quality control chart logic in terms of profile monitoring is integrated to construction of EWS to detect a coming global crisis. For this purpose, we use the reality that if there is a crisis, there should be loss in GDP which is the real cost of a crisis and consumption is the main component of GDP where primary energy consumption is a good indicator of it both in terms of industry and individuals' side reflecting their wealth. Thus, as a pilot study, we investigated whether a crisis can be detected by monitoring the relation between GDP and primary energy consumption. The annual data of G8 countries except Russia and big emerging countries except Poland, between the years 1980-2012, are examined. When the regression lines are fitted, it is observed that the model parameters are autocorrelated through time which violates control chart assumptions. To overcome this difficulty, we modeled them by well known ARIMA models that yield independent residuals. Then, the monitoring scheme is based on these residuals for each parameter, separately. At this stage, two alternative schemes namely Shewhart and EWMA, are considered and seen that EWMA is better to capture the 2008 global crisis although both couldn't detect the 1997 Asian crisis. However, this is an expected result since it was more local compared to 2008 crisis that affected both developed and emerging countries. Besides, the alert was seen three years before the crisis which gives quite time to policymakers to search for the reasons and take preventive actions. Of course, the other relations among monetary variables have to be considered for saying that it is about a coming crises. But this primitive initial study shows that it is a promising technique. Thus, as a future study, other relations have to be examined as well as the extension of the countries so that more local crises can be detected as well. Further, inclusion of more explanatory variables, common to all countries, would yield more precise and timely results in assessing the direction and timing of crises and/or structural change periods.

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