University of Piraeus

Department of Banking & Financial Management
MSc Program in Banking and Financial Management

Thesis

Super exogeneity and the Lucas Critique: Structural Invariance and Economic Policy

An empirical analysis for the market model

Zacharopoulou Sofia

Supervisor: N.Pittis

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1. INTRODUCTION

The use of econometric models for the purpose of policy analysis should be made with caution as Lucas argues in his seminal 1976 paper. He pointed out that it is of fundamental importance to establish that econometric models are invariant to possible policy interventions[1] prior to use them for policy analysis, since in the opposite case models may be potentially prone to ″structural breaks″[2] when regimes describing the function of the economy alter and thus the subsequent conclusions would be invalidated. Lucas made it clear that, if the economy can be characterized adequately as a stochastic dynamic environment with optimizing agents, then it is possible that the parameters of an estimated econometric model will not be invariant to changes either in the expectations-generating mechanisms or in policy rules.

The so-called Lucas critique is a testable empirical hypothesis since Engle et al.(1983) introduced the concept of *superexogeneity*, arguing that it could be used to test the empirical relevance of the Lucas Critique. In the case that superexogeneity hypothesis is rejected then this is evidence in favour of the Lucas Critique.

This study investigates empirically the validity of the superexogeneity assumption in the framework of the market model which is widely used for estimating the systematic risk of a stock through its beta parameter. It is based on the stylized fact that beta is unstable through time and aims in providing a theoretical interpretation of this by linking this instability to a possible rejection of the superexogeneity assumption of the market index's returns for the parameter beta. Such a finding would mean that regime switches in the GM (generating mechanism) of market index's returns are "passed through" to the GM of equities' returns and this is reflected by the instability of beta.

The structure of the study is the following:

- ✓ In section 2, the Lucas Critique and the concept of superexogeneity are further discussed.

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[1] Possible interventions include changes in monetary, fiscal, and exchange-rate policy rules, deregulation, financial and technological innovation and war.

[2] A model $f(x,\theta_t)$ has a break at time t_0 if :

$\theta_t = \theta_0 \quad t \leq t_0$

$\theta_t = \theta_1 \quad t > t_0$

where $\theta_0 \neq \theta_1$.Clearly θ_t could be a vector and there could be several breaks.

- ✓ In section 3, relative literature on testing the superexogeneity assumption is cited.
- ✓ In section 4, an econometric model based on the market model and consistent with the theoretical assumptions of efficient market hypothesis and the commonly empirical finding of volatility clustering in market index and stocks returns is formulated. Subsequently, the sufficient conditions for the superexogeneity of the market index returns for the beta coefficient are examined.
- ✓ In section 5, the methodological procedure employed for empirically testing the superexogeneity assumption in the aforementioned model for various countries, namely: U.S.A, U.K., Germany and Japan, is stated.
- ✓ In section 6, the empirical results are presented.
- ✓ Finally, section 7 summarizes the conclusions of the study.

2.1. THE LUCAS CRITIQUE

For most of the 20th century, economics has led the social sciences in developing and applying statistical techniques, often for the expressed purpose of predicting the consequences of economic policy. Yet, in spite of more than a half century of distinguished development, econometrics has had disappointing practical success and many visible failures.

When econometrics was at its zenith, Lucas offered a theoretical critique that could explain some of the disappointing performance of statistical analysis in economics.

The main point of the critique may be summarised in the following quote (Lucas 1976):

"*Given that the structure of an econometric model consists of optimal decision rules for economic agents, and that optimal decision rules vary systematically with changes in the structure of series relevant to the decision maker, it follows that any change in policy will systematically alter the structure of econometric models*."

The critique by Lucas argues that it is difficult to determine optimal macroeconomic policies because the announcement of these policies results in changes in behavior by economic agents and thus in changes in the parameters on which the optimal policy was based. Since parameter estimates are not invariant to changes in the policy

regimes, such estimates are therefore useless for forecasting the impact of the policy changes.

Lucas motivated his critique with four observations: ″frequent″ refitting of econometric relationships, intercept adjustments in forecasting, the empirically superior forecasts by models with randomly varying coefficients, and the exclusion (in modelling) of data prior to 1947, even though such data should be informative. All four observations could arise from empirical model misspecification of the sort described by Lucas.

The Lucas Critique is the consequence of *rational expectations* theory, which assumes optimizing economic agents, fully informed about the operation of the economy and possessing unbiased knowledge about all future economic developments.

In essence, the issue is whether an econometric model isolates ″invariants″ of the economic process.

2.2. DEFINITIONS OF WEAK, STRONG AND SUPER EXOGENEITY

The exogeneity of a variable means that it can be taken as ″given″ without loss of information for the purpose at hand:

1. For conducting ″efficient″ [3] statistical inference (estimation & testing), weak exogeneity is needed to hold
2. For reliable forecasting , strong exogeneity is necessary
3. For the purposes of policy analysis, superexogeneity is required.

Valid exogeneity assumptions may permit simpler modeling strategies, reduce computational expense, and help isolate invariants of the economic mechanism. Invalid exogeneity assumptions may lead to inefficient or inconsistent inferences and result in misleading forecasts and policy simulations. Exogeneity thus plays a key role throughout economic and econometric analysis, both theoretical and applied.

We proceed in defining the concepts of weak, strong and super exogeneity.

Let $z_t \in R^n$ be a vector of observable random variables at time t that characterize an economy. Observations for t=1…T are available.

By Z_t^1, we denote the t×n matrix: $Z_t^1 = (z_{1\ldots}\ z_t)$ and Z^0 represent the matrix of initial conditions. The analysis is conducted conditionally on Z^0.

[3] without loss of relevant information

The information available at time t is given by: $Z_{t-1} = \begin{bmatrix} Z_0 \\ Z^1_{t-1} \end{bmatrix}$

The process generating the T observations is represented by the joint data density function : $D(Z^1_t|Z^0,\theta)$, $\theta \in \Theta \subset R^n$

The vector z_t is partitioned into: $z_t = \begin{bmatrix} y_t \\ x_t \end{bmatrix}$, $y_t \in R^p$, $x_t \in R^q$, $p+q= n$.

Often the objective of empirical econometrics is to model how the observation z_t is generated conditionally on the past, so we factorize the joint data density as:

$$D(Z^1_t |Z^0, \theta)= \prod_{t=1}^{T} D(z_t|Z_{t-1},\theta)$$

and focus attention on the conditional density functions:

$$D(z_t|Z_{t-1},\theta) = D(y_t, x_t |Z_{t-1},\theta)= D(y_t | x_t, Z_{t-1},\theta) \cdot D(x_t|Z_{t-1},\theta)$$

The partitioning of z_t into y_t and x_t implies similar partitioning of parameter vectors.

Hence, the original model parameters θ are transformed to the parameters λ as $\lambda=g(\theta)$.The function $g(\cdot)$ defines a one-to-one mapping of θ into λ for $\lambda \in \Lambda$,sustaining that $\lambda = \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix}$ and corresponding to the factorization of the joint density into a conditional density and a marginal density:

$$D(z_t|Z_{t-1}, \theta) =D(y_t | x_t , Z_{t-1}, \lambda_1) \cdot D(x_t| Z_{t-1}, \lambda_2).$$

Such a factorization can always be achieved if λ_1 and λ_2 are defined to support it, although the resulting parameters may then be linked.

Whether or not conditional estimation will result in a loss of information depends crucially on the parameters that we focus our attention on (parameters of interest).

1. <u>Definition of weak exogeneity:</u>

x_t is weakly exogenous for the parameters of interest ψ if and only if

i. $\psi= \psi(\lambda_1)$, that is , ψ being a function of λ_1 alone (ψ not necessarily a 1-1 function) and

ii. λ_1 and λ_2 are variation free, $(\lambda_1 \times \lambda_2) \in \Lambda_1 \times \Lambda_2$ (i.e. λ_1 and λ_2 should not be subject to cross restrictions).

Thus, the parameter space of λ must be the cartesian product of the parameter spaces of the components vectors, so that the parameter space λ_1 does not depend on λ_2.Expressed slightly differently, knowledge about the value of one parameter provides no information on the other parameter's range of potential values.

When x_t is weakly exogenous for the parameters of interest ψ, there is no loss of information from estimating ψ in the conditional model $D(y_t| x_t, Z_{t-1}, \lambda_1)$ without modeling the marginal process determining x_t. Such a property simplifies the analysis, reduces its dimensionality and increases its robustness to potential misspecifications of the marginal model.

2. Definition of strong exogeneity:

x_t is strongly exogenous for the parameters of interest ψ if and only if

i. x_t is weakly exogenous for the parameters of interest ψ and

ii. y does not Granger cause x, that is : $D(x_t|Z_{t-1}, \lambda_2)= D(x_t|X_{t-1},Y_0, \lambda_2)$ (lags of y_t do not predict x_t)

When x_t is strongly exogenous for the parameters of interest ψ:

i. weak exogeneity ensures that the specification of the marginal process of x_t is not necessary for estimating ψ and

ii. Granger noncausality permits x_t to be regarded as ″given″ for forecasting future values of y_t (y_{t+j}) conditional on x_{t+j} and Z_{t+j-1} (statements about future values of y_t will not be vitiated by intermediate y_{t+k} altering x_{t+j} ($k<j$) i.e. there is no feedback from y_t to x_t).

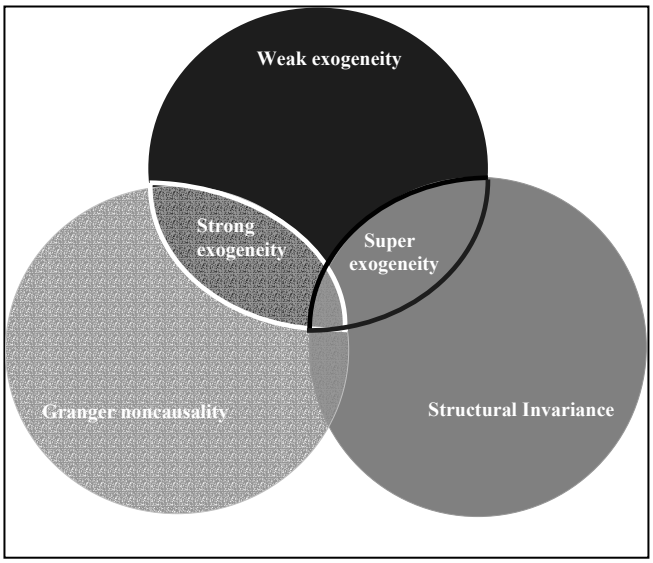
3. Definition of super exogeneity:

A parameter is invariant for a class of interventions if it remains constant under these interventions. If this property holds for all the parameters of a model, then this model is invariant for such interventions. A conditional model is structurally invariant if all its parameters are invariant for any change in the distribution of the conditioning variables. Consequently, x_t is super exogenous for the parameters of interest ψ if and only if:

i. x_t is weakly exogenous for the parameters of interest ψ and

ii. the conditional model $D(y_t | x_t , Z_{t-1}, \lambda_1)$ is structurally invariant

The relationship between weak, strong and super exogeneity appears in the following Venn diagram:



It is important to make three notices regarding the definition of superexogeneity:

1. For x_t to be super exogenous with respect to the parameters of interest ψ, the conditional model $D(y_t \mid x_t, Z_{t-1}, \lambda_1)$ must be structurally invariant even though ψ may depend only on a subvector of λ_1.
2. Weak exogeneity is neither sufficient nor necessary for structural invariance:
   - Not sufficient: Weak exogeneity of the conditioning variables does not rule out the possibility that economic agents change their behaviour in relation to interventions. That is, even though the parameters of interest and nuisance parameters (λ_2) are variation free over any given regime, where a regime is characterized by a fixed distribution of the conditioning variables, their variation between regimes may be related.
   - Not necessary: Conditional model may be structurally invariant without its parameters providing an estimate of the parameters of interest.
3. Superexogeneity requires weak exogeneity but not strong exogeneity. That is a vital weakening of the conditions required for empirical models to be useful for economic policy analyses. Since governments monitor the economy and usually base their policies on the past outcomes of the variables they seek to influence, strong exogeneity is an unlikely condition for policy variables.

The empirical presence of superexogeneity refutes the Lucas critique in practice; hence testing superexogeneity assumption makes it possible to discriminate between models affected by the critique and models which can be used for policy simulation purposes.

To present the link between superexogeneity and the Lucas critique, 3 levels of applicability of any critique addressed to claimed invariance should be distinguished.

Let y_t denote the variables about which agents form plans such that they implement their decisions at time t, given information I_{t-1} .The claimed invariant parameters of the decision rules relating y_t to I_{t-1} are denoted by θ.Then, the following three levels of critique could be applied to θ:

(a) θ will vary directly with changes in the environment

(b) θ will vary with changes in economic policy control rules

(c) θ will vary with changes in the environment which alter expectations.

A critique at level (a) is intended to entail the claim that there may exist sufficiently large changes in the environment such that empirical evidence embodied in econometric parameters ceases to be relevant. This level reflects the fact that total invariance of econometric models to all possible changes in the environment cannot be achieved in a social science: econometric models reflect modifiable human behaviour, their laws and institutions. When estimated from observations before a radical change in the state of nature, models cannot in general be expected to function equally well after the change has occurred. This fact limits but does not vitiate econometrics.

A critique at level (b) concerns potential variations in the parameters of econometric models in response to changes in the distributions of variables which are under the control of a governmental agency such as a central bank. Variables such as tax rates and interest rates may be manipulated by a policy agency to achieve their aims and thereby alter the parameters θ which are defined to be of interest by the economist. Expectations are not necessarily involved, since the behavior being modeled may be conditional or feedback only. If the behavior being modeled is one following forward-looking rules then the critique at level (c) is also relevant. The conjunction of the critique at level (b) with the critique at level (c) entails the Lucas critique and since when the critique at level (b) is invalid means that the regressors are superexogenous,

then it is clear that the empirical presence of superexogeneity refutes the Lucas critique in practice.

The claim that a model has invariant parameters over a given class of interventions is a claim that can be refuted by a single counter example, but cannot be confirmed by any number of corroborating instances i.e. any particular instance of parameter variation suffices to reject invariance while failing to confirm one instance of the critique cannot preclude the existence of other instances that provide evidence in favour of the critique.

The assumption of superexogeneity is testable if it is known that the parameters of the marginal distribution have changed over the sample period. A test for changes in the parameters of the conditional distribution could be interpreted as a test for superexogeneity with respect to the particular interventions observed. It should be pointed out that false rejection of the null of superexogeneity may be induced by misspecifications in the marginal model.

2.3. TESTING SUPEREXOGENEITY

Whether x_t is exogenous depends *inter alia* upon the process generating y_t and x_t, so exogeneity may be testable.

Superexogeneity requires weak exogeneity of x_t for the parameters of interest ψ, and invariance of the conditional model's parameters (λ_1) to changes in the parameters of the marginal process (λ_2).Thus, a common test for superexogeneity, when the weak exogeneity assumption is satisfied, is as follows:

Establish the constancy of λ_1 and the nonconstancy of λ_2. With λ_1 constant and λ_2 not, then λ_1 must be invariant to λ_2 and so super exogeneity holds.(Hendry 1988)

Tests for parameter constancy thus are central to tests of super exogeneity. Recursive estimation is an incisive tool for investigating parameter constancy, both through the sequence of estimated coefficient values and through the associated tests for constancy.

Recursive estimation was preferred in our study to the testing procedure suggested by Engle and Hendry (1993) because it was not applicable to our model due to the existence of ARCH models in both the marginal and conditional models. Nevertheless, we provide a brief description of it because it is used quite extensively in empirical literature. The main points of this test are the following:

1. First, having established the constancy of λ_1 and the nonconstancy of λ_2 we respecify the marginal model until its parameters become constant. This is possible if the instability is the result of specific interventions at particular points in time. Under these circumstances the use of dummy variables may be sufficient to explain the time variation of the parameters.
2. Then, these dummy variables are introduced in the conditional model and tested for their significance. Their insignificance demonstrates invariance of the conditional model to the specified changes in the marginal model.

3. TESTING SUPEREXOGENEITY LITERATURE

Empirical applications of superexogeneity tests include:

- Andreas M. Fisher, Journal of Monetary Economics (1989)

Using weekly data spanning from 1977 to 1985 concerning U.S.A. he examined monetary expectations and policy regime changes and concluded that under the assumption that the variance is constant, the data evidence is found to reject superexogeneity.

- Katarina Juselius, Journal of Policy Modeling (1992)

Using quarterly data spanning from 1974 to 1987 concerning Denmark she examined domestic and foreign effects on prices in an open economy and concluded that the empirical results strongly favored a backward-looking behavioral model in terms of structurally stable parameters as opposed to a forward-looking expectations model. The results stand up as quite strong evidence against the Lucas critique.

- Hildegart Ahumada, Journal of Policy Modeling (1992)

Using monthly data spanning from 1977 to 1988 concerning Argentina he examined the demand for currency, income and inflation and concluded that the conditional model of real cash balances appears constant, so the empirically nonconstant univariate marginal models for inflation and the interest rate imply the super exogeneity of those variables in the conditional model.

- Gunnar Bårdsen, Journal of Policy Modeling (1992)

Using quarterly data spanning from 1967 to 1989 concerning Norway he examined the demand for narrow money, prices, real expenditure and interest rates and concluded that prices, real expenditure and interest rates are superexogenous for the parameters of the demand for money.

- Ragnar Nymoen, Journal of Policy Modeling (1992)

Using annually data spanning from 1960 to 1987 concerning Finland he examined manufacturing real wages and concluded that the Lucas Critique was refuted for the model estimated.

- A.S. Hurn, & V.A. Muscatelli, Oxford Bulletin of Economics and Statistics (1992)

Using annually data spanning from 1966 to 1989 concerning U.K. they examined the demand for broad money (M4), wealth, GDP & interest rates and concluded that the rejection of the Lucas critique need not imply that economic agents are not forward-looking. One possible explanation is that economic agents, whilst forward-looking, use data-based predictors, instead of using formal models to forecast the evolution of economic variables of interest.

- Guglielmo Caporale, Applied Economics (1996)

Using quarterly data spanning from 1962 to 1993 concerning U.K., from 1973-1992 concerning Germany, from 1972-1992 concerning France & Italy he examined wages, CPI, Aggregate productivity and unemployment and concluded that in all cases the conditional model is not affected by the first and second moments of the residuals from the marginal models. This invariance result implies that the estimated linear regression models are not subject to the Lucas critique over the period examined. There also appear to be some significant differences between the European economies, both in the long-run structure and in the dynamics of wage determination, which can plausibly be attributed to the bargaining environment. As one would expect, the legal and institutional framework in which wage bargains are made does affect the outcome.

4. THE ECONOMETRIC MODEL

This study examines the superexogeneity assumption in the market model framework. The market model posits a linear relationship between the returns from a given stock and the returns from some market portfolio. This model has been widely used, particularly in event study methodology, in tests for market efficiency and as a basis for testing the capital asset pricing model.

In many typical applications the statistical assumptions underlying the market model are often assumed rather than tested for their validity. However, much attention

has been raised recently on the stability of the parameters of the model, in particular that of the slope coefficient, the beta-parameter.

The beta is widely known for its role in capturing a stock's sensitivity to movements of the market as a whole. A stock with a beta greater than one is expected to rise more than the market on a market upturn, but also to fall more than the market on a market downturn. Stocks with beta's less than one are typically more defensive. By contrast they are expected to rise less than the market on a market upturn and to fall less than the market on a market downturn. The beta also serves an important role in risk quantification and turns out to be the primary determinant of the market risk exposure of a stock. As such it has the potential to become an invaluable tool to investment managers for the purposes of controlling risk.

In order to examine the stability of beta under alternative paths of the return of market index model we consider the following model:

Let z_t be a bivariate process with $z_t = [\, R_t^i, R_t^m \,]$, where R_t^i = the return of stock i at time t and R_t^m = the return of the market index at time t.

The joint distribution of Z_t conditional on past values under the assumptions of stationarity and Markovness of order one equals:

$$D(Z_t \,|Z_{t-1},\varphi) = \Pi\, D(z_t \,|z_{t-1},\theta) = \Pi\, D(R_t^i \mid R_t^m, z_{t-1}, \lambda_1)\; D(R_t^m \mid z_{t-1}, \lambda_2) \quad (1)$$

Under the additional assumption of linearity and taking into consideration the efficient market hypothesis and the volatility clustering in stock returns and market index returns, the following models, corresponding to the conditional and marginal components of (1), arise:

$$\left.\begin{array}{l} E(R_t^i \mid R_t^m, z_{t-1}) = a + b\, R_t^m \\ var(R_t^i \mid R_t^m, z_{t-1}) = c_0 + c_1 \left(u_{t-1}\right)^2 \\ \lambda_1 = (a, b, c_0, c_1) \\ E(R_t^m \mid z_{t-1}) = 0 \\ var(R_t^m \mid z_{t-1}) = d_0 + d_1 \left(R_{t-1}^m\right)^2 \\ \lambda_2 = (d_0, d_1) \end{array}\right\} \; R_t^i = a + b\, R_t^m + u_t \;,\; u_t \sim \text{MD-ARCH(1)}$$

The absence of past values in both means is in accordance with the market efficiency hypothesis and ARCH models are adopted so as the conditional variances capture the volatility dynamics present in the stock markets. The use of the ARCH technique in the market model is suggested *inter alia* by Bera, A., Bubnys, E. & Park, H. (1988).

The beta parameter equals: $b = \frac{\text{cov}(R_t^i, R_t^m)}{\text{var}(R_t^m)}$ and the conditional variance for the market index return implies that the unconditional variance equals: $\text{var}(R_t^m) = \frac{d_0}{1\text{-}d_1}$.

To examine whether structural shifts in the marginal model of R_t^m can discredit the conditional model of R_t^i by destabilizing the estimated coefficient beta through time, is equal to examine if the conditioning variable $\left(R_t^m\right)$ is superexogenous for the parameter b or not.

For the market index return $\left(R_t^m\right)$ to be superexogenous for the parameter of interest b the two following conditions must hold:

i) The market index return must be weakly exogenous for the parameter b, which is equivalent to:

i_a) parameter b must be a function of λ_1 alone and

i_b) λ_1 and λ_2 must be variation free, that is: $(\lambda_1 \times \lambda_2) \in \Lambda_1 \times \Lambda_2$

ii) The conditional model $D(R_t^i \mid R_t^m, z_{t-1}, \lambda_1)$ must be structurally invariant; all its parameters must be invariant for any change in the distribution of the conditioning variable $\left(R_t^m\right)$.

The market index return is weakly exogenous for the parameter beta since beta is an exclusive function of λ_1 (as it coincides with one of the parameters constituting the vector λ_1) and the variation freeness is also satisfied while the property of structural invariance needs to be tested and it will hold if λ_1 remains unaffected when λ_2 or a subvector of it change.

For parameter beta for example since, $\text{var}(R_t^m) = \frac{d_0}{1\text{-}d_1}$ and $b = \frac{\text{cov}(R_t^i, R_t^m)}{\text{var}(R_t^m)}$ this condition holds when $\text{cov}(R_t^i, R_t^m)$ responds to changes in $\text{var}(R_t^m)$, induced by the

changes in d_0 and/or d_1, in a way that offsets these changes and consequently resulting to a stable parameter b i.e. $cov(R_t^i , R_t^m)=b\ var(R_t^m) , \forall\ t$.

5. METHODOLOGY

We examined the validity of the market index return's superexogeneity assumption for the parameter beta, in the framework of the market model, for the following countries: U.S.A, U.K., Germany and Japan. Our data set contained weekly observations on the S&P 500, the London Stock Exchange FTSE 100, DAX 30 and NIKKEI 225 indexes and on the prices of 10 ″blue chips″ stocks covering the period from 18/01/1984 to 21/01/2004.

The countries included in our study were selected on the grounds of market efficiency attributed to the high liquidity and the liberalization present in their stock markets.

The selection of the stocks was conducted according to the following criteria:

- All stocks have remained constituents of the corresponding index for each country throughout the period 18/01/1984-21/01/2004.
- In order to achieve diversification of our sample of stocks we attempted to include stocks from as many economic sectors as possible.

The selected stocks are the following:

Selected stocks & corresponding sector of activity

U.S.A									
Bank of America	**AT&T**	**Bausch& Lomb**	**Coca-Cola**	**Du Pont**	**Edison Intl.**	**Exxon Mobil**	**IBM**	**Mc Donald's**	**General Electric**
Financial	**Telecom-munication Services**	**Health Care**	**Consumer Staples**	**Materials**	**Utilities**	**Energy**	**Information Technology**	**Consumer Discretionary**	**Industrial**
U.K.									
British American Tobacco	**Cable& Wireless**	**Glaxo Smith Kline**	**Marks& Spencer Group**	**Royal Bank of Scotland**	**TESCO**	**Unilever**	**Cadburry Scheweppes**	**Hilton Group**	**BAE Systems**
Tobacco	**Telecom-munication Services**	**Pharma-ceuticals**	**General Retailers**	**Financial**	**Food & Drug Retailers**	**Food Producers & Processors**	**Food Producers & Processors**	**Leisure Entertainment & Hotels**	**Aerospace & Defence**
GERMANY									
BASF	**BAYER**	**Deutsche Bank**	**Lufthansa**	**Man**	**RWE**	**Schering**	**Siemens**	**Thyssenkrupp**	**Volkswagen**
Chemical	**Chemical**	**Financial**	**Airlines**	**Engineer**	**Power company utilities**	**Pharma-ceutical**	**Electronic engineer**	**Engineer**	**Automobile Industry**
JAPAN									
Toyota Motor Corp.	**Matsushita Electric INDL**	**SONY**	**Fuji Photo Fims**	**Sapporo HDG**	**Nippon Steel**	**Mitsubishi Heavy Industries**	**Kawasaki Heavy Industries**	**Bank of Yokohama**	**Tokyo Electric Power**
Automobile Industry	**Electric Machinery**	**Electric Machinery**	**Chemical**	**Food Producer**	**Steel Products**	**Machinery**	**Shipbuilding**	**Financial**	**Power**

The 20–year sample period covers many non-firm-specific economic events and thus provides an excellent opportunity to test the superexogeneity assumption in the market model.

The aforementioned model was employed in the data after transforming them to returns and "E-Views" program was used for estimation purposes. Subsequently, a superexogeneity test through recursive estimating of the coefficients was conducted. Recursive estimation was used as a general diagnostic tool to detect signs of parameter nonconstancy over the sample period.

The recursive procedure can be described as follows:

In recursive estimation the model is estimated repeatedly, using ever larger subsets of the sample data. If there are k coefficients to be estimated in the parameter vector, then the first k observations are used to form the first estimate of the parameter vector. The next observation is then added to the data set and k+1 observations are used to compute the second estimate of the parameter vector. This process is repeated until all the T sample points have been used, yielding T-k+1 estimates of the parameter vector. The view of all the recursive coefficient estimates enables us to trace the evolution of estimates for any coefficient as more and more of the sample data are used in the estimation. If the coefficient displays significant variation as more data is added to the estimating equation, it is a strong indication of instability. In the case of structural breaks these coefficient plots will show jumps.

If structural breaks in λ_2 are found to be reflected in structural changes in λ_1, demonstrated by coinciding jumps in recursive coefficients plots, then the data do not provide any evidence in favour of the superexogeneity assumption.

In order to examine stability in λ_1 and λ_2 research for parameters a and b was confined to recursive estimates plots while for parameters c_0, c_1, d_0 and d_1 further statistical inference was made possible after considering the AR(1) transformation of an ARCH(1) process[4]. So, parameter stability of c_0, c_1, d_0 and d_1 was in addition examined applying recursive residuals, CUSUM, CUSUM of SQUARES and one-step forecast tests.

Recursive residuals, CUSUM, CUSUM of SQUARES tests and the plots of recursive estimates of coefficients served primarily as graphical devices to reveal

[4] A proof for the equivalent ARMA(r,p) form of a GARCH(p,q) model is provided in the appendix.

nonconstancy in general while one-step forecast test was used in order to detect specific dates of breaks in parameters.

Dates of breaks were detected rather than supposed known because of the following critique that this practice has received:

If the dates of structural change are selected by appeal to events known a priori, then it is essential that the researcher can argue that the events are selected exogenously (independently of the data) otherwise conventional critical values are invalid and inference misleading.

Even when it is *known*, treating the break dates as given may be invalid: the occurrence and size of the break may be determined in part by other economic factors, thereby making the break stochastic.

The detection of break dates excludes the use of stability tests that require a priori knowledge of when a break appears in the sample such as the Chow-type stability tests.

The description of recursive residuals, CUSUM, CUSUM of SQUARES and one-step forecast tests follows.

5.1. Recursive Residuals test

At each step of recursive estimation the last estimates can be used to predict the next value of the dependent variable. The one-step ahead forecast error resulting from this prediction, suitably scaled, is defined to be a recursive residual.

More formally, let X_{t-1} denote the $(t-1)\times k$ matrix of the regressors from period 1 to period t-1, and y_{t-1} the corresponding vector of observations on the dependent variable. These data up to period t-1 give an estimated coefficient vector, denoted by b_{t-1}. This coefficient vector gives you a forecast of the dependent variable in period t. The forecast is $x'_t b_{t-1}$, where x'_t is the row vector of observations on the regressors in period t. The forecast error is $y_t - x'_t b_{t-1}$, and the forecast variance is given by:

$$\sigma^2 \left(1+x'_t \left(X'_t X_t\right)^{-1} x_t\right) \qquad (5.1.1)$$

The recursive residual w_t is defined as:

$$w_t = \frac{\left(y_t - x'_t b_{t-1}\right)}{\left(1+x'_t \left(X'_t X_t\right)^{-1} x_t\right)^{1/2}} \qquad (5.1.2)$$

These residuals can be computed for t = k+1,…,T. If the maintained model is valid, the recursive residuals will be independently and normally distributed with zero mean and constant variance σ^2.

The plot of the recursive residuals about the zero line accompanied with plus and minus two standard errors at each point may then be used to conclude for the stability of the parameters. Residuals outside the standard error bands suggest instability in the parameters of the equation.

5.2. CUSUM test

The CUSUM test (Brown, Durbin, and Evans, 1975) is based on the cumulative sum of the recursive residuals. The plot of the cumulative sum together with the 5% critical lines is used to test the model for parameter stability. The test finds parameter instability if the cumulative sum goes outside the area between the two critical lines.
The CUSUM test is based on the statistic:

$$W_t = \sum_{r=k+1}^{t} \frac{w_r}{s} \qquad (5.2.1)$$

for t=k+1,…,T, where w is the recursive residual defined above, and s is the standard error of the regression fitted to all T sample points. If the b vector remains constant from period to period, $E\left(W_t\right)=0$, but if b changes, W_t will tend to diverge from the zero mean value line. The significance of any departure from the zero line is assessed by reference to a pair of 5% significance lines, the distance between which increases with t. The 5% significance lines are found by connecting the points:

$$\left[k,\pm\text{-}0.948\left(T\text{-}k\right)^{1/2}\right] \quad \text{and} \quad \left[T,\pm 3\times 0.948\left(T\text{-}k\right)^{1/2}\right] \qquad (5.2.2)$$

Movement of W_t outside the critical lines is suggestive of coefficient instability.

5.3. CUSUM of Squares test

The CUSUM of squares test (Brown, Durbin, and Evans, 1975) is based on the test statistic:

$$S_t=\left(\sum_{r=k+1}^{t} w_r^2\right)/\left(\sum_{r=k+1}^{T} w_r^2\right) \qquad (5.3.1)$$

The expected value of S under the hypothesis of parameter constancy is:

$$E(S_t)=(t-k)/(T-k) \qquad (5.3.2)$$

which goes from zero at t=k to unity at t=T. The significance of the departure of S from its expected value is assessed by reference to a pair of parallel straight lines around the expected value. The CUSUM of squares test consists of a plot of S_t against t and of the pair of 5% critical lines. As with the CUSUM test, movement outside the critical lines is suggestive of parameter or variance instability.

5.4. One-Step Forecast Test

The one-step forecast test is based on the recursive residuals defined above. As it has already been stated, in the case of stability the recursive residuals are independently and normally distributed with zero mean and constant variance σ^2 .Standardized recursive residuals are defined as:

$$w_t^{st}=\frac{(y_t - x'_t b_{t-1})}{\hat{\sigma}\left(1+x'_t (X'_t X_t)^{-1} x_t\right)^{1/2}} \qquad (5.4.1)$$

and they are distributed as:

$$w_t^{st} \sim t_{T-k} \qquad (5.4.2)$$

or asymptotically distributed as:

$$w_t^{st} \sim N(0,1) \qquad (5.4.3)$$

The dates corresponding to standardized recursive residuals with p-value less than 0.05 were considered as dates of a break.

The superexogeneity assumption was tested by comparing the break dates for the parameters of the market index returns model with these for the parameters of the

conditional model. Even the coincidence of only one break date in the parameters of the marginal and the conditional model suffices to reject the superexogeneity assumption since as it was mentioned before invariance claims are generically refutable: any particular instance is enough evidence against invariance.

The dates of break for the parameters of the market index returns model were then associated with major events that can be characterized as interventions.

6. EMPIRICAL RESULTS

6.1. The data and preliminary evidence

Data set was obtained from DataStream database and contains weekly observations on the S&P 500, the London Stock Exchange FTSE 100, DAX 30 and NIKKEI 225 indexes and on the prices of 10 ″blue chips″ stocks covering the period from 18/01/1984 to 21/01/2004.The model introduced in section 4 employs the returns of stocks and market indexes. Thus, our original data set was transformed to returns using the following formula:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \times (100) \qquad (6.1)$$

where p_t stands for price at time t and r_t is the return at time t. Dividends are ignored or supposed reinvested.

Preliminary testing of the data confirms the stationarity of the series under scrutiny, as anticipated for stock and market indexes returns. This result is in accordance with the stationarity assumption underlying our model. Stationarity was tested through the Augmented Dickey-Fuller (ADF) unit root test after examining the series for the existence of a constant or trend and deciding that none is necessary either under the null hypothesis of unit-root or the alternative hypothesis of stationarity.

As the ADF test relies on a parametric approach to deal with serial correlation and heterogeneity, its power is questionable. We therefore also test for unit roots using the Phillips-Perron test (Phillips 1987; Phillips and Perron 1988). The iid assumption of the ADF test is relaxed in the Phillips-Perron test procedure, which imposes much weaker conditions on the error term. The Phillips-Perron test is thus robust to time-dependent heteroskedasticity like the ARCH(1) adopted in our model. The results of the two tests are similar, clearly rejecting the null hypothesis of non-stationarity. The results of the unit root tests are summarised in table 1:

Unit root testing: ADF test (no constant & trend, lag length selection: Akaike information criterion)

U.S.A.

	S&P 500	Bank of America	AT&T	Bausch&Lomb	Coca-Cola	Du Pont	Edison Int	Exxon-Mobil	IBM	Mc Donald's	General Electric
Test statistic	-10.67	-9.71	-33.13	-33.87	-33.23	-24.26	-6.71	-38.44	-9.88	-12.17	-33.78

U.K.

	FTSE100	British American Tobacco	Cable&Wireless	GlaxoSmithKline	Marks& Spencer Group	Royal Bank of Scotland	TESCO	Unilever	Cadburry Scheweppes	Hilton Group	BAE Systems
Test statistic	-12.40	-34.90	-34.29	-17.81	-24.80	-35.01	-36.55	-20.14	-34.94	-10.11	-7.60

GERMANY

	DAX30	BASF	BAYER	Deutsche Bank	Lufthansa	Man	RWE	Schering	Siemens	Thyssenkrupp	Volkswagen
Test statistic	-16.68	-22.66	-11.56	-9.81	-22.12	-33.38	-32.60	-21.48	-15.77	-32.96	-8.82

JAPAN

	Nikkei225	Toyota Motor Corp	Matsushita Electric INDL	Sony Corp.	Fuji Photo Fims	Sapporo HDG	Nippon Steel	Mitsubishi	Kawasaki	Bank of Yokohama	Tokyo Electric Power
Test statistic	-16.11	-34.76	-35.41	-31.45	-35.36	-33.18	-35.36	-34.05	-15.42	-35.01	-32.21

Unit root testing: Phillips-Perron test (no constant & trend, spectral estimation method: Bartlett Kernel, bandwidth: Newey-West)

U.S.A.

	S&P 500	Bank of America	AT&T	Bausch&Lomb	Coca-Cola	Du Pont	Edison Int	Exxon-Mobil	IBM	Mc Donald's	General Electric
Test statistic	-33.72	-32.62	-33.13	-33.89	-33.22	-32.32	-30.83	-38.57	-30.13	-33.94	-33.80

U.K.

	FTSE100	British American Tobacco	Cable&Wireless	GlaxoSmithKline	Marks& Spencer Group	Royal Bank of Scotland	TESCO	Unilever	Cadburry Scheweppes	Hilton Group	BAE Systems
Test statistic	-32.77	-34.83	-34.29	-34.81	-34.23	-35.02	-36.77	-33.56	-35.08	-34.93	-34.61

GERMANY

	DAX30	BASF	BAYER	Deutsche Bank	Lufthansa	Man	RWE	Schering	Siemens	Thyssenkrupp	Volkswagen
Test statistic	-33.79	-35.34	-34.76	-32.88	-33.22	-33.37	-32.98	-33.04	-32.26	-33.01	-33.57

JAPAN

	Nikkei225	Toyota Motor Corp	Matsushita Electric INDL	Sony Corp.	Fuji Photo Fims	Sapporo HDG	Nippon Steel	Mitsubishi	Kawasaki	Bank of Yokohama	Tokyo Electric Power
Test statistic	-33.01	-35.23	-35.51	-31.44	-36.24	-33.18	-35.22	-34.03	-34.85	-34.92	-32.21

Critical values: 1% = -2.57, 5% = -1.94, 10% =-1.62

Table 1

Regarding the ARCH assumption embedded in our model, data provide evidence in favour of it, as demonstrated in tables 2 to 6.

The deviation of the descriptive statistics from the values that a Normal distribution exhibits (Skewness=0, Kurtosis=3) suggests that the distributions of weekly market indexes and stocks returns are asymmetric and leptokurtic relative to the Normal distribution. The autoregressive conditional heteroskedastic (ARCH) process, suggested by an extensive bibliography for modeling the conditional volatility of asset prices returns, may well be able to explain this kind of behaviour of the distributions and in addition it captures the volatility clustering present in them. The use of the ARCH model is being further reinforced by the p-values of the Jarque-Bera statistic that reject the null hypothesis of Normality for the weekly unconditional distribution of market indexes returns and the p-values of the ARCH LM test statistic for the residuals from OLS estimation of the market model.

Weekly unconditional distribution of market indexes returns					
	Mean	Variance	Skewness	Kurtosis	Jarque-Bera (p-value)
U.S.A					
S & P 500	0.00210	0.00050	-0.4470	6.6124	0
U.K.					
FTSE 100	0.00166	0.00054	-0.3094	9.3669	0
GERMANY					
DAX 30	0.00206	0.00095	-0.3924	6.7838	0
JAPAN					
NIKKEI 225	0.00050	0.00084	-0.0673	4.6009	0
sample size: 1045(18/01/1984 - 21/01/2004)					

Table 2

Distribution of residuals (OLS estimation of the market model)					
U.S.A					
	Mean	Variance	Skewness	Kurtosis	ARCH LM test (p-value) lag=1
Bank of America	-3.69E-18	0.00124	0.2440	6.629	0.000554
AT & T	-4.60E-18	0.00140	0.4204	9.461	0.000118
Bausch & Lomb	-5.51E-18	0.00155	-0.9590	13.973	0.103110
Coca-Cola	1.05E-18	0.00089	-0.0386	6.067	0.002217
Du Pont	-4.17E-18	0.00079	0.1094	5.739	0.000011
Edison Intl	-2.57E-18	0.00160	0.5837	27.391	0.088551
Exxon-Mobil	-3.11E-18	0.00056	-0.0226	4.278	0
IBM	-2.70E-18	0.00111	0.3955	7.460	0.008697
McDonalds	-3.41E-18	0.00100	0.1407	5.108	0.047927
General Electric	1.85E-18	0.00122	0.1056	5.882	0
sample size: 1045(18/01/1984 - 21/01/2004)					

Table 3

Distribution of residuals (OLS estimation of the market model)					
U.K.					
	Mean	Variance	Skewness	Kurtosis	ARCH LM test (p-value) lag=1
British American Tobacco	-1.01E-18	0.00159	1.5589	16.404	0.102756
Cable & Wireless	2.17E-18	0.00223	-0.7351	19.880	0.004897
GlaxoSmithKline	-5.51E-19	0.00108	0.5345	6.166	0.004937
Marks & Spencer Group	1.09E-18	0.00105	0.0090	5.431	0
Royal Bank of Scotland	2.84E-18	0.00130	0.5130	4.899	0.000059
TESCO	2.21E-19	0.00113	0.3969	4.563	0.000023
Unilever	-3.82E-18	0.00089	-0.0358	7.882	0
Cadburry Scheweppes	2.23E-18	0.00102	0.8914	8.953	0.000264
Hilton Group	5.58E-19	0.00165	0.6387	10.092	0.082265
BAE Systems	-7.05E-19	0.00257	-0.4921	16.245	0.013727
sample size: 1045(18/01/1984 - 21/01/2004)					

Table 4

Distribution of residuals (OLS estimation of the market model)					
GERMANY					
	Mean	Variance	Skewness	Kurtosis	ARCH LM test (p-value) lag=1
BASF	-2.59E-19	0.00060	-0.0022	5.750	0.016196
Bayer	-1.72E-18	0.00066	-0.5911	9.067	0.021164
Deutsche Bank	1.97E-18	0.00065	0.5668	9.402	0.000747
Lufthansa	-2.08E-18	0.00135	0.1979	3.977	0.000173
MAN	-1.93E-18	0.00119	0.2232	4.122	0
RWE	-3.34E-18	0.00090	0.3669	6.082	0
Schering	-4.92E-19	0.00088	0.2275	6.004	0.003306
Siemens	-3.00E-18	0.00070	0.8190	12.403	0.000067
Thyssenkrupp	-9.57E-19	0.00108	-0.0621	5.453	0
Volkswagen	-9.70E-19	0.00104	0.2837	4.778	0.005630
sample size: 1045(18/01/1984 - 21/01/2004)					

Table 5

Distribution of residuals (OLS estimation of the market model)					
JAPAN					
	Mean	Variance	Skewness	Kurtosis	ARCH LM test (p-value) lag=1
Toyota Motor Corp	-1.90E-18	0.00122	0.8145	6.202	0
Matsushita Electric INDL	-1.44E-18	0.00129	0.6999	5.885	0.000662
SONY	2.17E-18	0.00164	0.6762	7.596	0
Fuji Photo Films	-2.76E-18	0.04005	0.6057	6.770	0.000002
SAPPORO HDG	7.53E-19	0.00125	0.7608	9.116	0
Nippon Steel	3.02E-19	0.00146	0.7045	6.064	0
Mitsubishi Heavy Industries	1.31E-18	0.00147	0.1004	5.303	0
Kawasaki Heavy Industries	4.11E-18	0.00269	1.4835	13.038	0
Bank of Yokohama	1.70E-18	0.00223	1.0978	8.767	0
Tokyo Electric Power	1.25E-18	0.00139	1.2543	8.430	0
sample size: 1045(18/01/1984 - 21/01/2004)					

Table 6

6.2. Estimation of the model

Consequently, we proceed in the full sample ARCH estimation of our model and we employ the ARCH-LM test to verify that our data do not exhibit any additional ARCH.

The ARCH LM test statistic is computed from an auxiliary test regression. To test the null hypothesis that there is no ARCH up to order q in the residuals, we run the regression:

$$e_t^2 = \beta_0 + \sum_{s=1}^{q} \beta_s e_{t-s}^2 + u_t \qquad (6.2)$$

where e is the residual. The reported F-statistic is an omitted variable test for the joint significance of all lagged squared residuals.

The test rejects the null hypothesis of ARCH effect of higher order left in the standardized residuals of our estimated models. Tables from 7 to 11 summarize the results:

ARCH(1) estimation of market indexes returns			
	c_0	c_1	ARCH LM test(p-value) lag=1
U.S.A			
S & P 500	0.000371	0.264592	0.99
U.K.			
FTSE 100	0.000390	0.255511	0.45
GERMANY			
DAX 30	0.000689	0.267498	0.36
JAPAN			
NIKKEI 225	0.000707	0.157604	0.64
sample size: 1045(18/01/1984 - 21/01/2004)			

Table 7

ARCH(1) estimation of the market model					
U.S.A					
	a	b	c_0	c_1	ARCH LM test (p-value) lag=1
Bank of America	0.001126	1.184427	0.001122	0.095517	0.71
AT & T	0.000065	0.837623	0.000954	0.383831	0.16
Bausch & Lomb	0.001107	1.018208	0.001299	0.195709	0.64
Coca-Cola	0.001971	0.775025	0.000778	0.131850	0.74
Du Pont	0.000187	0.949272	0.000692	0.119582	0.76
Edison Intl	0.002030	0.341247	0.000555	1.243634	0.06
Exxon-Mobil	0.001189	0.544527	0.000485	0.132772	0.81
IBM	0.000148	1.014033	0.000935	0.170104	0.69
McDonalds	0.001442	0.882430	0.000861	0.153488	0.30
General Electric	0.003410	-0.093164	0.000952	0.214263	0.57
sample size: 1045(18/01/1984 - 21/01/2004)					

Table 8

ARCH(1) estimation of the market model					
U.K.					
	a	b	c_0	c_1	ARCH LM test (p-value) lag=1
British American Tobacco	0.002740	0.731777	0.001362	0.171717	0.69
Cable & Wireless	-0.00018	1.434970	0.001184	0.683583	0.22
GlaxoSmithKline	0.001983	0.964993	0.000856	0.228738	0.33
Marks & Spencer Group	0.000228	0.856771	0.000912	0.122995	0.60
Royal Bank of Scotland	0.002210	1.179676	0.001116	0.141602	0.80
TESCO	0.002003	0.721776	0.000916	0.196331	0.58
Unilever	0.001739	0.771397	0.000712	0.210539	0.61
Cadburry Scheweppes	0.000259	0.737489	0.000829	0.204899	0.47
Hilton Group	0.000356	1.128300	0.001494	0.097661	0.86
BAE Systems	0.000579	0.889610	0.001722	0.440859	0.40
sample size: 1045(18/01/1984 - 21/01/2004)					

Table 9

ARCH(1) estimation of the market model					
GERMANY					
	a	b	c_0	c_1	ARCH LM test (p-value) lag=1
BASF	0.000125	0.813483	0.000482	0.232078	0.32
Bayer	-0.000450	0.911457	0.000495	0.302587	0.59
Deutsche Bank	0.000104	1.031329	0.000502	0.267782	0.44
Lufthansa	0.000029	0.962842	0.001185	0.118978	0.91
MAN	0.000434	0.977257	0.000962	0.193589	0.73
RWE	0.000426	0.726193	0.000720	0.200224	0.61
Schering	0.001279	0.656064	0.000713	0.215234	0.36
Siemens	-0.000346	1.053265	0.000423	0.564388	0.39
Thyssenkrupp	0.001373	0.996787	0.000787	0.292184	0.36
Volkswagen	0.000088	1.069755	0.000904	0.133540	0.66
sample size: 1045(18/01/1984 - 21/01/2004)					

Table 10

ARCH(1) estimation of the market model					
JAPAN					
	a	b	c_0	c_1	ARCH LM test (p-value) lag=1
Toyota Motor Corp	0.001865	0.725738	0.000829	0.330697	0.78
Matsushita Electric INDL	0.000812	0.833137	0.001142	0.110496	0.96
SONY	0.000988	0.908279	0.001265	0.243402	0.91
Fuji Photo Films	0.001047	0.724100	0.001197	0.199189	0.39
SAPPORO HDG	0.000157	0.717671	0.000897	0.285246	0.98
Nippon Steel	0.000249	0.888242	0.001013	0.307218	0.62
Mitsubishi Heavy Ind.	0.000611	0.859969	0.001105	0.266319	0.52
Kawasaki Heavy Ind.	0.002137	1.117614	0.001665	0.449894	0.25
Bank of Yokohama	0.001805	0.704271	0.001734	0.227071	0.69
Tokyo Electric Power	0.000442	0.442574	0.000939	0.395020	0.64
sample size: 1045(18/01/1984 - 21/01/2004)					

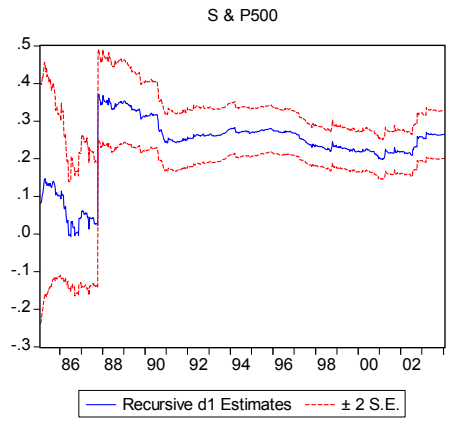
Table 11

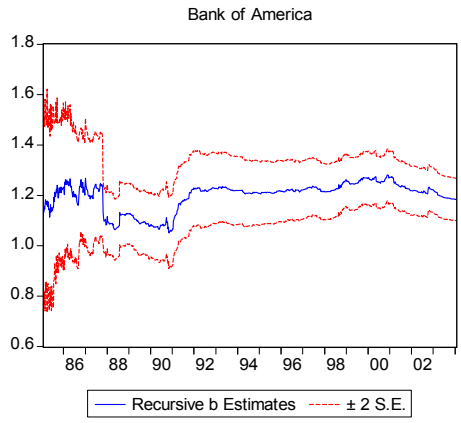
6.3. Superexogeneity testing

Stability in parameter vectors λ_1 and λ_2 was first examined by recursively estimating the model adding one observation each time. The first 50 estimates were ignored because the sample up to the 50th observation might be inadequate to produce reliable estimates. As a result, the plots of recursive estimates include estimates and the corresponding standard errors for the period from 6/02/1985 to 21/01/2004.

The plots of recursive estimates were suggestive of instability for all the parameters under consideration. It is important to notice that the necessary condition for conducting a superexogeneity test which is the instability of the parameters of the marginal model is satisfied.

Since for every country examined almost all stocks seem to have at least one break date in common with their market index we have overwhelming evidence against the superexogeneity assumption. For example, in the case of the returns of S&P 500 and Bank of America the following plots depicts the fact that recursive estimates of d_1 and b share a break date at the end of 1987:





Further stability testing was made possible for parameters c_0, c_1, d_0 and d_1 after considering the AR(1) transformation of an ARCH(1) process. The equivalence between the two processes is demonstrated by the following relationships:

- marginal model:

$$\left.\begin{array}{l} E(R_t^m \mid z_{t-1}) = 0 \\ var(R_t^m|z_{t-1}) = d_0 + d_1 \left(R_{t-1}^m\right)^2 \\ \lambda_2 = (d_0, d_1) \end{array}\right\} \; R_t^m \sim \text{MD-ARCH(1)}$$

$$R_t^m \sim \text{MD-ARCH(1)} \rightarrow \left(R_t^m\right)^2 \sim \text{AR(1)} \rightarrow \left(R_t^m\right)^2 = d_0 + d_1 \left(R_{t-1}^m\right)^2 + \varepsilon_t, \varepsilon_t \sim \text{white noise}$$

- conditional model:

$$\left.\begin{array}{l} E(R_t^i \mid R_t^m, z_{t-1}) = a + b\ R_t^m \\ var(R_t^i \mid R_t^m, z_{t-1}) = c_0 + c_1 \left(u_{t-1}\right)^2 \\ \lambda_1 = (a, b, c_0, c_1) \end{array}\right\} R_t^i = a\ + b\ R_t^m + u_t\ ,\ u_t \sim \text{MD-ARCH(1)}$$

$$u_t \sim \text{MD-ARCH(1)} \rightarrow \left(u_t\right)^2 \sim \text{AR(1)} \rightarrow \left(u_t\right)^2 = c_0 + c_1 \left(u_{t-1}\right)^2 + e_t\ ,\ e_t \sim \text{white noise}$$

Ordinary Least Squares (OLS) estimation of the AR(1) processes allowed the application of recursive residuals, CUSUM, CUSUM of SQUARES and one-step forecast tests in the parameters c_0, c_1, d_0 and d_1.All these tests were indicative of instability for the parameters of both the marginal and conditional models. The CUSUM test in some cases does not reject the null hypothesis of stability but this finding can be justified by the low power of the test as Hansen (1991) pointed out.

Consequently, through a simple program executed using "E-views" software the p-values of standardized recursive residuals were reported. The dates corresponding to standardized recursive residuals with p-value less than 0.05 were then considered as dates of a break. The superexogeneity assumption was tested by comparing the break dates for the parameters of the market index returns model with these for the parameters of the conditional model. Since, in our sample of 40 equities 37 were found to have at least one break date in common with their market index, we concluded that the superexogeneity assumption was rejected.

The dates of break for the parameters of the market index returns model which were related to the rejection of superexogeneity were then linked to major events, such as general elections or fiscal and monetary changes in an attempt to determine the interventions that catalyzed the breaks. These events were chosen with regard to factors which are generally considered that alter the regime of uncertainty in equity markets.

Tables 12 to 15 provide information about the rejection of superexogeneity as they include the break dates that led to this rejection.

U.S.A.

Coinciding break dates										
S&P 500	Bank of America	AT&T	Bausch&Lomb	Coca-Cola	Du Pont	Edison Intl	Exxon-Mobil	IBM	McDonalds	General Electric
21/10/1987	21/10/1987									21/10/1987
02/09/1998				02/09/1998						
21/10/1998			21/10/1998							
22/03/2000							22/03/2000			
20/12/2000		20/12/2000			20/12/2000					
03/10/2001	03/10/2001					03/10/2001	03/10/2001			
31/07/2002										31/07/2002
16/10/2002	16/10/2002			16/10/2002				16/10/2002		
19/03/2003									19/03/2003	

Table 12

In the case of the S&P500 index the break dates were explained by the following events:

- 21/10/1987:This date is clearly related to the stock market crash of 19/10/1987.
- 02/09/1998:Russia devalues and defaults on 17/08/1998 and subsequently cause escalating concerns for Latin America.
- 21/10/1998:Surprise inter-meeting Fed rate cut on 15/10/1998 .
- 22/03/2000:Fed increased rates on 22/03/2000.
- 20/12/2000:On 13/12/2000 George Bush was confirmed as president.
- 03/10/2001:On 03/10/2001 American central bankers decided to push overnight loan rates down by a half-point to 2.5 percent, the lowest level since 1962, in a bid to restore confidence to the economy damaged by the terrorist attacks on 11/09/2001 in New York and Washington.
- 31/07/2002:President Bush's signed on 30/07/2002 a corporate fraud bill designed to make it more difficult for company executives to deceive investors.
- 16/10/2002:On 16/10/2002 General Kofi Annan publicly supported a new Security Council resolution to toughen the UN weapons inspectors' mandate thus a warn was addressed to Iraq that it had a last chance to comply.
- 19/03/2003:President Bush declared on 17/03/2003 that Saddam had 48hrs to choose exile or face war.

U.K.

Coinciding break dates										
FTSE100	British American Tobacco	Cable&Wireless	GlaxoSmithKline	Marks& Spencer	Royal Bank of Scotland	Tesco	Unilever	Cadburry Scheweppes	Hilton Group	BAE Systems
28/10/1987	28/10/1987				28/10/1987					
04/11/1987								04/11/1987		
23/09/1992			23/09/1992						23/09/1992	23/09/1992
12/09/2001			12/09/2001						12/09/2001	
31/07/2002					31/07/2002		31/07/2002			
18/09/2002										18/09/2002
19/03/2003		19/03/2003								

Table 13

In the case of the FTSE100 index the break dates were explained by the following events:

- 28/10/1987&04/11/1987:These dates are clearly related to the stock market crash of 19/10/1987.
- 23/09/1992:Exchange Rate Mechanism (ERM) crisis on 16/09/1992;UK and Italy exit ERM.
- 12/09/2001:Terrorist attacks on 11/09/2001 in New York and Washington.
- 31/07/2002:Accounting irregularities emerge.
- 18/09/2002:Iraq on 16/09/2002 asserted that it would allow weapons inspectors back into the country "without conditions," but U.S. and other authorities were skeptical as to his intentions.
- 19/03/2003:President Bush declared on 17/03/2003 that Saddam had 48hrs to choose exile or face war.

GERMANY

Coinciding break dates										
Dax30	**BASF**	**BAYER**	**Deutsche Bank**	**Lufthansa**	**MAN**	**RWE**	**Schering**	**Siemens**	**Thyssenkrupp**	**Volkswagen**
08/01/1986			**08/01/1986**							
28/10/1987							**28/10/1987**			
11/11/1987							**11/11/1987**			
07/10/1998			**07/10/1998**			**07/10/1998**				
12/09/2001				**12/09/2001**						
03/10/2001				**03/10/2001**	**03/10/2001**		**03/10/2001**	**03/10/2001**		
24/07/2002										**24/07/2002**
16/10/2002		**16/10/2002**	**16/10/2002**		**16/10/2002**	**16/10/2002**	**16/10/2002**		**16/10/2002**	
19/03/2003	**19/03/2003**	**19/03/2003**								**19/03/2003**

Table 14

In the case of the DAX30 index the break dates were explained by the following events:

- 08/01/1986:On 01/01/1986 Spain and Portugal are 11th and 12th to join European Economic Community.
- 28/10/1987&11/11/1987:These dates are clearly related to the stock market crash of the 19/10/1987.
- 07/10/1998:General elections on 27/09/1998 were won by the socialist party (SPD).On 07/10/1998 it was announced that Oscar Lafontaine was to become the next Minister of Finance.
- 12/09/2001:Terrorist attacks on 11/09/2001 in New York and Washington.
- 03/10/2001:On 03/10/2001 American central bankers decided to push overnight loan rates down by a half-point to 2.5 percent, the lowest level since 1962, in a bid to restore confidence to the economy damaged by the terrorist attacks on 11/09/2001 in New York and Washington.
- 24/07/2002:Accounting irregularities emerge.
- 16/10/2002:The European Commission took aim at Germany, France and Portugal over excessive budget deficits and the slow pace of market liberalization.
- 19/03/2003:President Bush declared on 17/03/2003 that Saddam had 48hrs to choose exile or face war.

JAPAN

Coinciding break dates										
NIKKEI225	Toyota	Matsushita	SONY	FUJI	Sapporo HDG	Nippon Steel	Mitsubishi	Kawasaki	Bank of Yokohama	Tokyo Electric Power
17/09/1986	17/09/1986									
22/10/1986							22/10/1986			22/10/1986
24/12/1997					24/12/1997					
21/01/1998						21/01/1998			21/01/1998	
10/03/1999		10/03/1999	10/03/1999							
24/05/2000			24/05/2000			24/05/2000		24/05/2000		

Table 15

In the case of the NIKKEI225 index the break dates were explained by the following events:

- 17/09/1986:GATT (General Agreement on Trade and Tariffs) meeting:Multirateral Trade Negotiations, the Uruguay Round.
- 22/10/1986:UK "Big Bang" in financial sector.
- 24/12/1997:The Committee on Administrative Reform releases a final report which summarizes the progress of deregulation and administrative reform. As regards the financial system, the report recommends the urgent implementation of the specific topics pointed out in the so-called Japanese Big Bang. It also points out the necessity of further deregulation and reform of other institutional frameworks, such as the tax system and the legal system.
- 21/01/1998: The Minister of Finance releases a statement on the implementation of measures to make stock markets more fair and transparent. The measures include (1) stricter action by the Securities and Exchange Surveillance Commission against those engaging in unfair trading that can distort fair price formation ; (2) intensive monitoring by the Tokyo Stock Exchange of stocks with excessive price movements; (3) a review of the rules for short selling; and (4) stricter penalties set for market participants violating laws and regulations.
- 10/03/1999:Public funds (7.5 trillion yen) injected into major banks to recapitalize them, in the hope of inducing better lending behavior.
- 24/05/2000:The Bank of Japan's Policy Board is moving closer to raising rates for the first time in a decade and ending its unusual policy of guiding them to virtually zero, minutes from its meeting on April 10 showed. On 19/05/2000 the bank governor, Masaru Hayami, said that an interest rate rise was on the way.

6.4. Theoretical and empirical implications

Since the rejection of the superexogeneity assumption was established for the vast majority of the examined equities, we may conclude that it is a factor that accounts for the instability of the beta parameter in the version of the market model considered in our study.

We must notice that the rejection of the superexogeneity assumption of the market index returns for beta means that investors are forward-looking since a dynamic model with non-superexogenous contemporaneous variables reflects the behavior of forward-looking agents. This means that future expectations are embodied in the parameters of the market model. Since the market model is also a behavioral model because its underlying structure concerns optimization rules of individuals based on their preferences, the rejection of superexogeneity suggests that the market model's parameters become a mixture of behavioral parameters and future expectations.

This finding also implies that the Lucas Critique is relevant in the market model and that asset demand functions of individuals vary with regime shifts in the market index returns induced by interventions which affect their future expectations. Thus, every major event which occurs during the sample period and can possibly alter the equity market's state of uncertainty should be taken into consideration as a factor that might change the parameters of the market model.

The empirical implications of the rejection of the superexogeneity assumption include portfolio management considerations. In periods of regime shifts in the marginal model previous estimates of beta cannot be trusted for reasons of forming or reforming an efficient portfolio since underestimation/overestimation of the systematic risk the portfolio bears might be inferred.

The lack of superexogeneity in the market model has also important implications for event study methodology frequently applied in empirical studies of corporate finance. It may lead to spurious detection of abnormal returns if the sample period includes dates that breaks have occurred in the parameters of the model for the market index returns and beta is assumed stable rather than tested for its stability. As a result, event studies should be treated with caution as they may falsely suggest that a particular event had a significant effect on the equity price.

Another interesting result from our study was that the stability testing revealed the existence of breaks in the parameters of the market model that could not be interpreted by the violation of the superexogeneity assumption. Therefore, we can deduce that these breaks in the parameters may be associated with firm-specific events.

7. Conclusions

The main result of our study is the rejection of the superexogeneity assumption when it is tested in a market model framework. We used a data set comprised by the market indexes and 10 equities from U.S.A, U.K, Germany and Japan. We focused on the investigation of the structural invariance employing a variety of stability tests since the weak exogeneity assumption was intrinsic in our model. Contrary to the common practice of taking the break dates as known *a priori*, we detected them applying the one-step forecast test. Finally, we discussed the theoretical implications of the lack of superexogeneity and its empirical relevance in portfolio management and event study methodology.

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APPENDIX

1) Proof for the ARMA(r,q) representation of a GARCH(p,q) process.

Theorem: Let $\{\varepsilon_t\}$ ~ GARCH(p,q). Then $\{\varepsilon_t^2\}$ ~ARMA(r,p) ,r=max(p,q)

Proof:

The general formula for a GARCH(p,q) process is:

$$h_t^2 = k + \gamma_1 h_{t-1}^2 + \gamma_2 h_{t-2}^2 + ... + \gamma_p h_{t-p}^2 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + ... + \alpha_q \varepsilon_{t-q}^2$$

In order to prove the theorem we proceed as follows:

1st step: Add and subtract the term: $\gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \varepsilon_{t-2}^2 + ... + \gamma_p \varepsilon_{t-p}^2$

$$h_t^2 = k + \sum_{i=1}^{p} \gamma_i h_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 - \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 \Rightarrow$$

$$h_t^2 = k + \sum_{i=1}^{p} -\gamma_i \left(\varepsilon_{t-i}^2 - h_{t-i}^2 \right) + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

2nd step:Add the term ε_t^2 in both sides of the equation:

$$h_t^2 + \varepsilon_t^2 = k + \sum_{i=1}^{p} -\gamma_i \left(\varepsilon_{t-i}^2 - h_{t-i}^2 \right) + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \varepsilon_t^2 \Rightarrow$$

According to the relation above, the maximum length for the coefficients of the ε_{t-i}^2 terms would be r=max(p,q). Taking $\beta_i=\alpha_i+\gamma_i$ (when p>q, we will have that $\beta_i= \alpha_i$) we obtain that:

$$h_t^2 + \varepsilon_t^2 = k + \sum_{i=1}^{q} -\gamma_i \left(\varepsilon_{t-i}^2 - h_{t-i}^2 \right) + \sum_{i=1}^{r=\max(p,q)} \beta_i \varepsilon_{t-i}^2 + \varepsilon_t^2 \Rightarrow$$

$$\boxed{\varepsilon_t^2 = k + \sum_{i=1}^{p} -\gamma_i \left(\varepsilon_{t-i}^2 - h_{t-i}^2 \right) + \sum_{i=1}^{r=\max(p,q)} \beta_i \varepsilon_{t-i}^2 + \left(\varepsilon_t^2 - h_t^2 \right)} \quad \text{(A)}$$

Notice that h_t is the forecast of ε_t^2 based on its own lagged values and thus $w_t = \varepsilon_t^2 - h_t^2$ is the error associated with this forecast. Thus, w_t is a white noise process that is fundamental for ε_t^2.

This can also be depicted as:

$$\varepsilon_t^2 = E\left(\varepsilon_t^2 \middle| I_{t-1} \right) + w_t, w_t \sim WhiteNoise$$

$$\varepsilon_t^2 = \underbrace{E\left(\varepsilon_t^2 \middle| I_{t-1} \right)}_{h_t^2} + w_t \Rightarrow w_t = \varepsilon_t^2 - h_t^2$$

$$(A)\Rightarrow \boxed{\varepsilon_t^2 = k + \sum_{i=1}^{p} -\gamma_i w_{t-i} + \sum_{i=1}^{r=\max(p,q)} \beta_i \varepsilon_{t-i}^2 + w_t}$$

It becomes obvious that the last relation is an ARMA process in ε_t^2. This process would be stationary if all roots of the characteristic polynomial corresponding to the autoregressive part, which is of order r=max(p,q) and with coefficients $\beta_i = \alpha_i+\gamma_i$, are outside the unit circle.

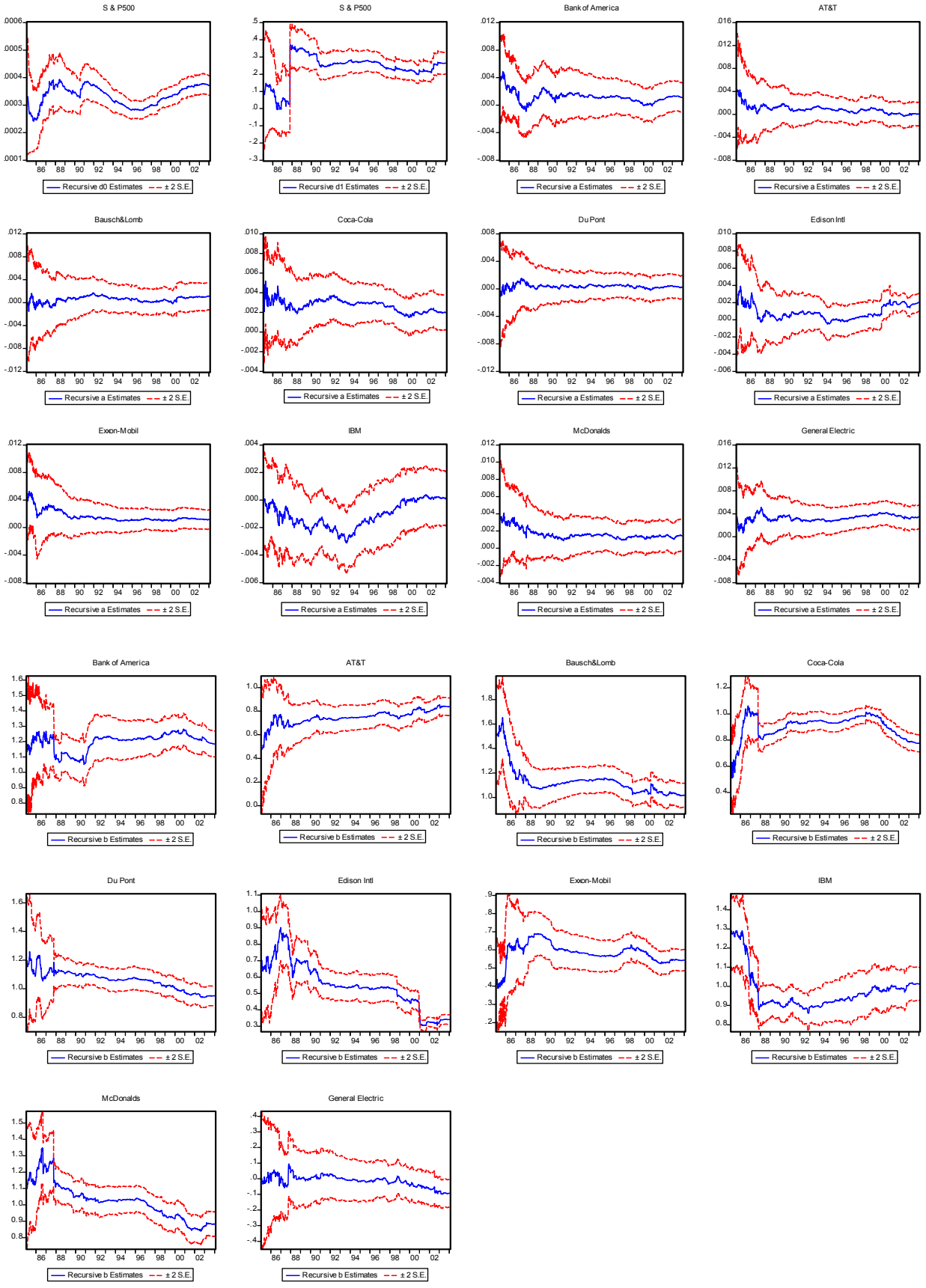
As the ARCH family of process is a subclass of the GARCH family, we can rewrite the ARCH(1) model for the ε_t series as a GARCH(0,1) process with conditional variance as:

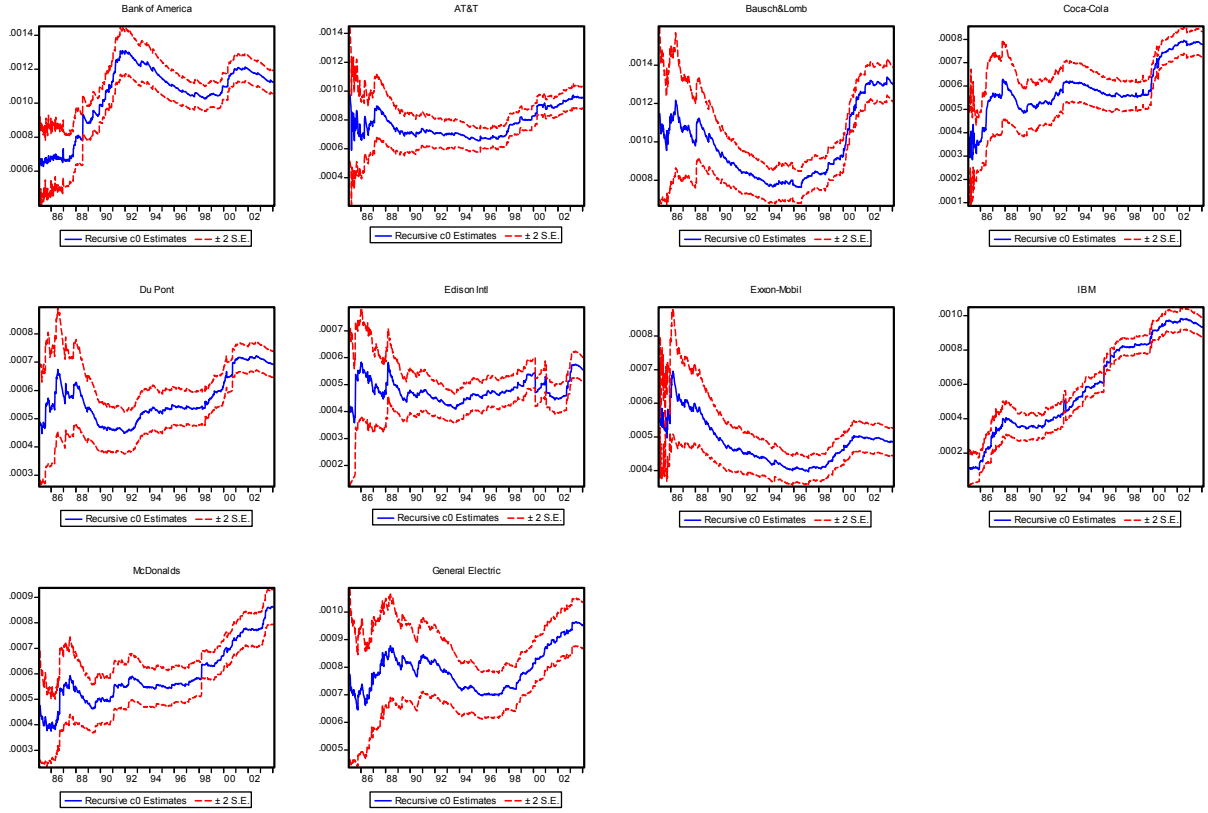
$$h_t^2 = k + \alpha_1 \varepsilon_{t-1}^2$$

According to the theorem, the ARCH(1) process can be transformed to an AR(1) process in ε_t^2, i.e.

$$\varepsilon_t^2 = k + \alpha_1 \varepsilon_{t-1}^2 + w_t$$

2) Recursive do & d1 estimates of the market index - Recursive a, b, c0 & c1 estimates of the stocks U.S.A

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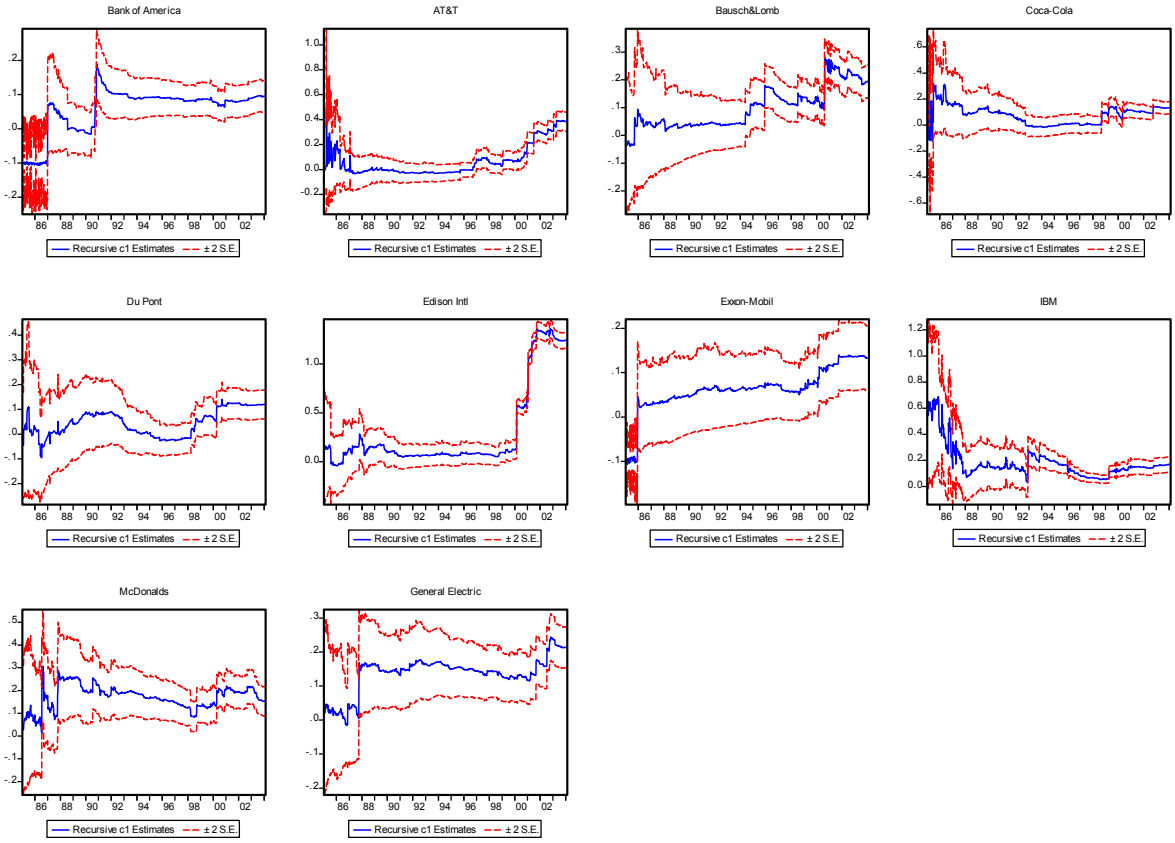
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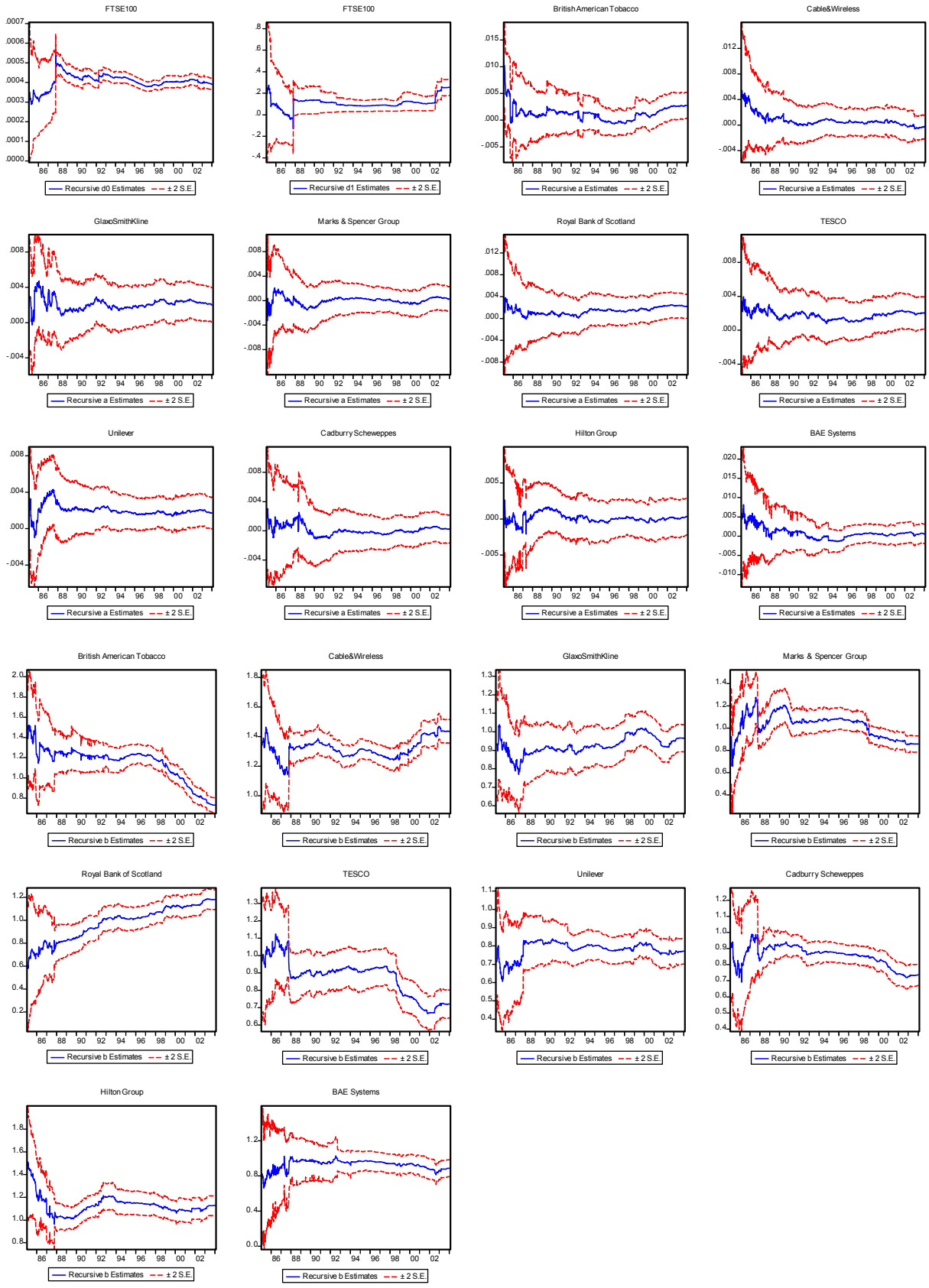
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British American Tobacco
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Cable&Wireless
Recursive a Estimates ± 2 S.E.
GlaxoSmithKline
Recursive a Estimates ± 2 S.E.
Marks & Spencer Group
Recursive a Estimates ± 2 S.E.
Royal Bank of Scotland
Recursive a Estimates ± 2 S.E.
TESCO
Recursive a Estimates ± 2 S.E.
Unilever
Recursive a Estimates ± 2 S.E.
Cadburry Scheweppes
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Hilton Group
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BAE Systems
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British American Tobacco
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Cable&Wireless
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GlaxoSmithKline
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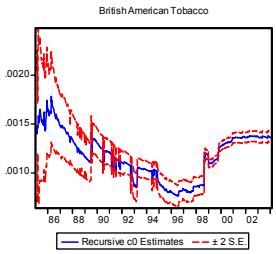
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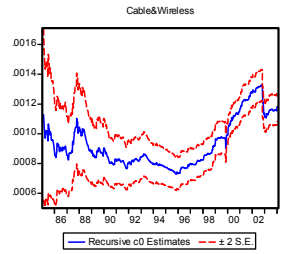
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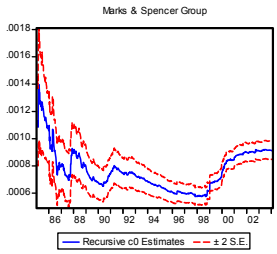
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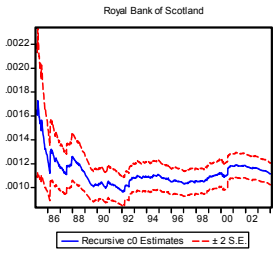
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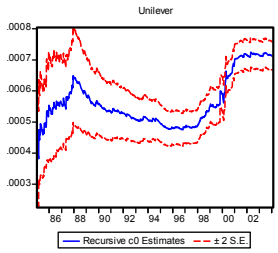
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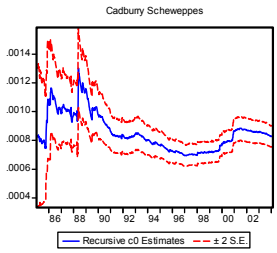
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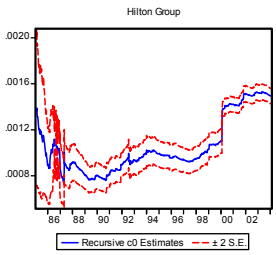
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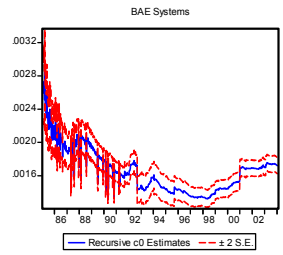
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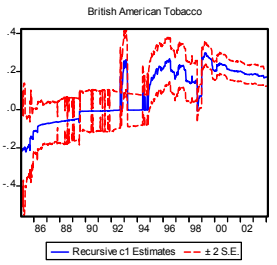
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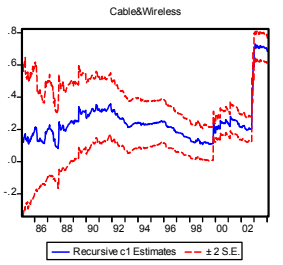
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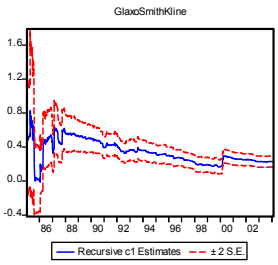
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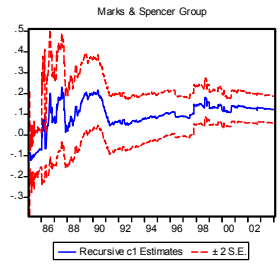
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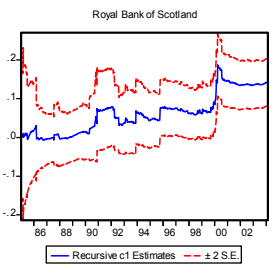
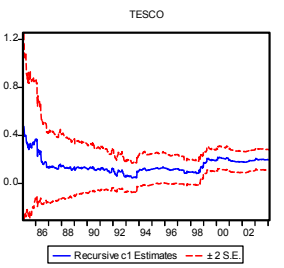
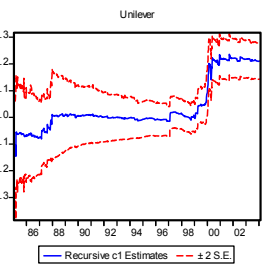
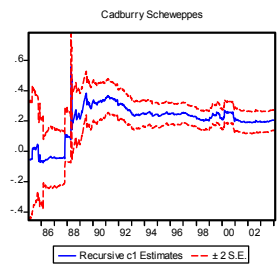
Recursive c1 Estimates
± 2 S.E.


Royal Bank of Scotland
Recursive c1 Estimates
± 2 S.E.


TESCO
Recursive c1 Estimates
± 2 S.E.


Unilever
Recursive c1 Estimates
± 2 S.E.


Cadburry Scheweppes
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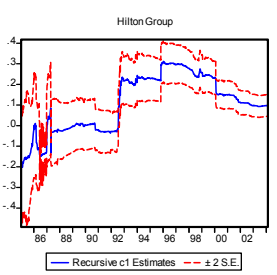
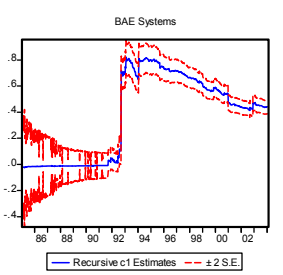
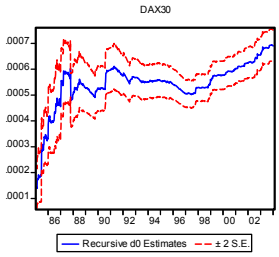
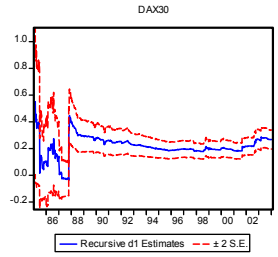
± 2 S.E.


Hilton Group
Recursive c1 Estimates
± 2 S.E.


BAE Systems
Recursive c1 Estimates
± 2 S.E.

GERMANY


DAX30
Recursive d0 Estimates ± 2 S.E.


DAX30
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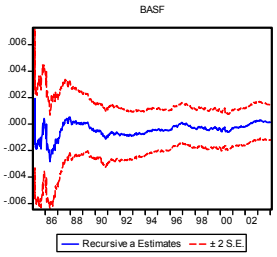
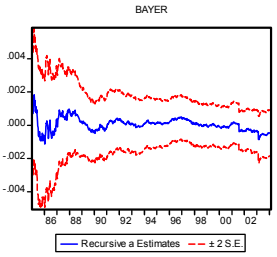
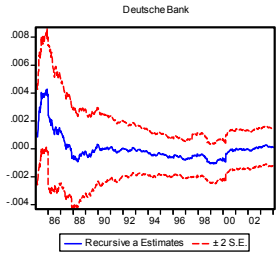
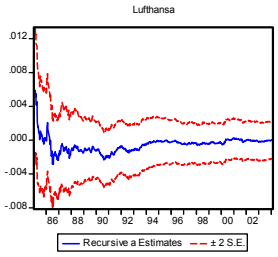
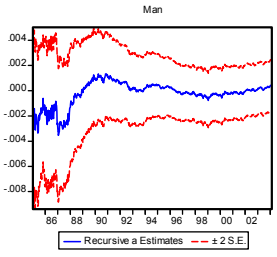
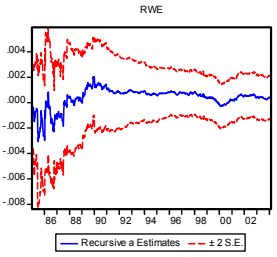

BASF
Recursive a Estimates ± 2 S.E.

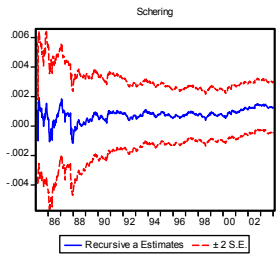

BAYER
Recursive a Estimates ± 2 S.E.

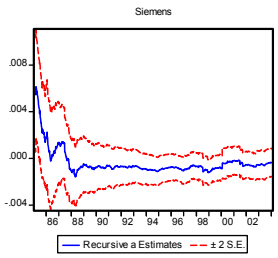

Deutsche Bank
Recursive a Estimates ± 2 S.E.

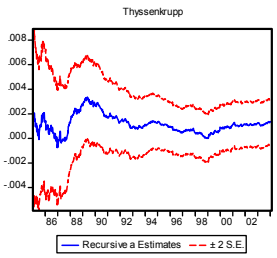

Lufthansa
Recursive a Estimates ± 2 S.E.

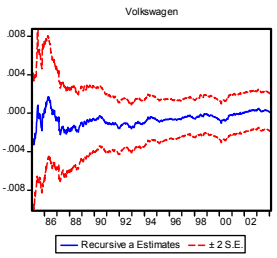

Man
Recursive a Estimates ± 2 S.E.

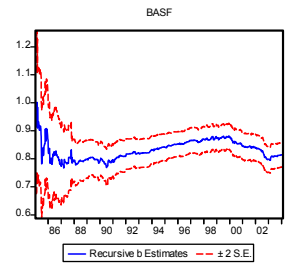

RWE
Recursive a Estimates ± 2 S.E.

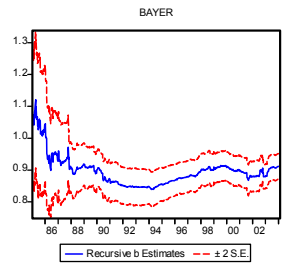

Schering
Recursive a Estimates ± 2 S.E.

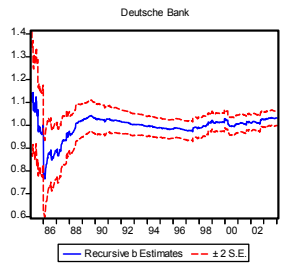

Siemens
Recursive a Estimates ± 2 S.E.

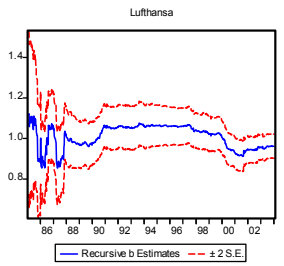

Thyssenkrupp
Recursive a Estimates ± 2 S.E.

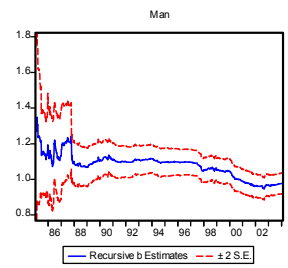

Volkswagen
Recursive a Estimates ± 2 S.E.

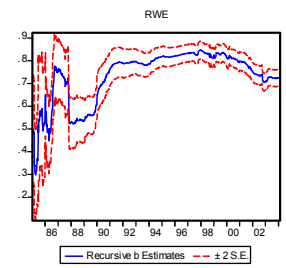

BASF
Recursive b Estimates ± 2 S.E.

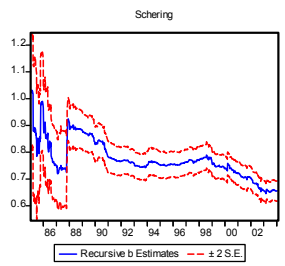

BAYER
Recursive b Estimates ± 2 S.E.

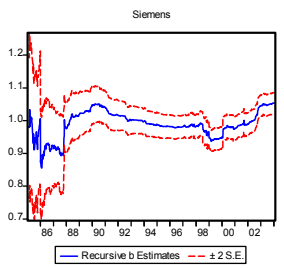

Deutsche Bank
Recursive b Estimates ± 2 S.E.

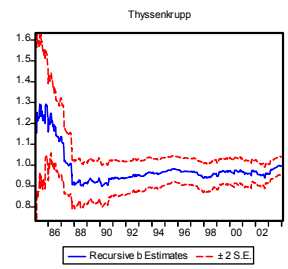

Lufthansa
Recursive b Estimates ± 2 S.E.

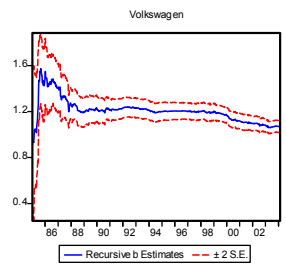

Man
Recursive b Estimates ± 2 S.E.

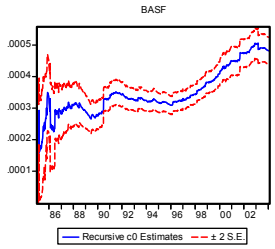

RWE
Recursive b Estimates ± 2 S.E.

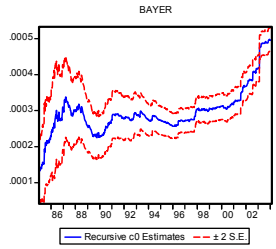

Schering
Recursive b Estimates ± 2 S.E.

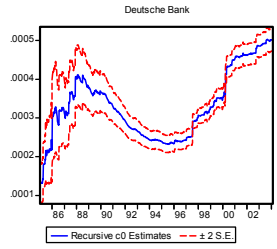

Siemens
Recursive b Estimates ± 2 S.E.

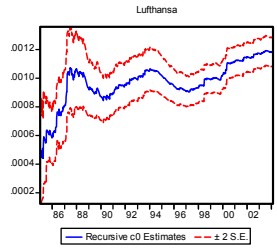

Thyssenkrupp
Recursive b Estimates ± 2 S.E.

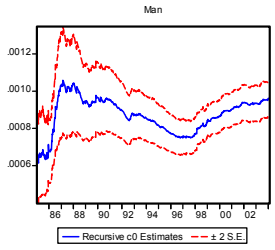

Volkswagen
Recursive b Estimates ± 2 S.E.

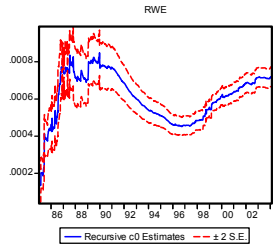

BASF
Recursive c0 Estimates
± 2 S.E.

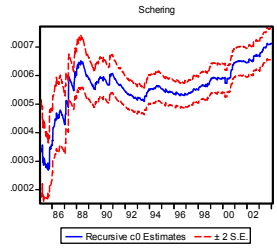

BAYER
Recursive c0 Estimates
± 2 S.E.

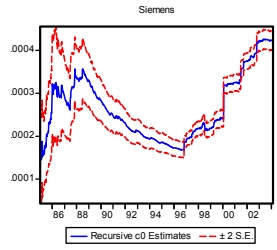

Deutsche Bank
Recursive c0 Estimates
± 2 S.E.

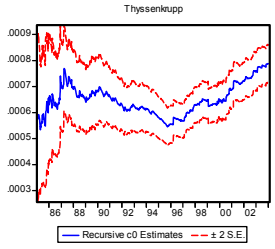

Lufthansa
Recursive c0 Estimates
± 2 S.E.

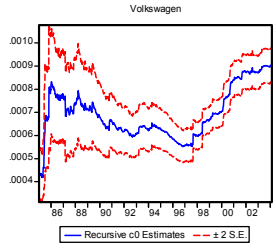

Man
Recursive c0 Estimates
± 2 S.E.

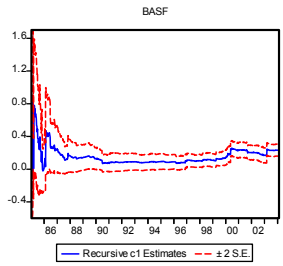

RWE
Recursive c0 Estimates
± 2 S.E.

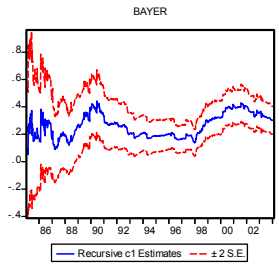

Schering
Recursive c0 Estimates
± 2 S.E.

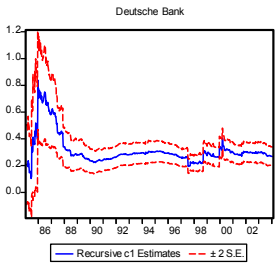

Siemens
Recursive c0 Estimates
± 2 S.E.

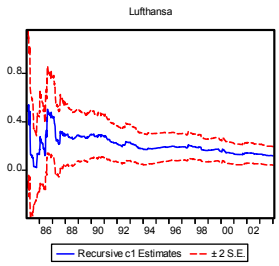

Thyssenkrupp
Recursive c0 Estimates
± 2 S.E.

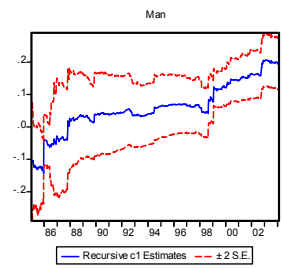

Volkswagen
Recursive c0 Estimates
± 2 S.E.

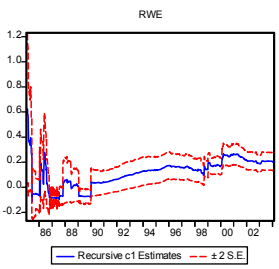

BASF
Recursive c1 Estimates
± 2 S.E.

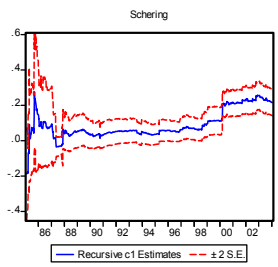

BAYER
Recursive c1 Estimates
± 2 S.E.

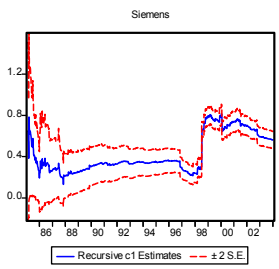

Deutsche Bank
Recursive c1 Estimates
± 2 S.E.

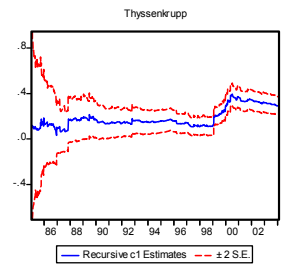

Lufthansa
Recursive c1 Estimates
± 2 S.E.

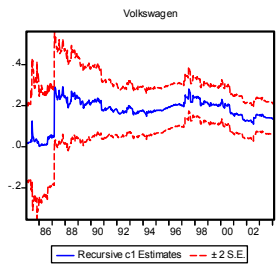

Man
Recursive c1 Estimates
± 2 S.E.


RWE
Recursive c1 Estimates
± 2 S.E.


Schering
Recursive c1 Estimates
± 2 S.E.

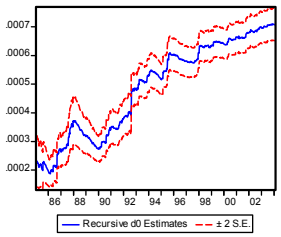

Siemens
Recursive c1 Estimates
± 2 S.E.


Thyssenkrupp
Recursive c1 Estimates
± 2 S.E.

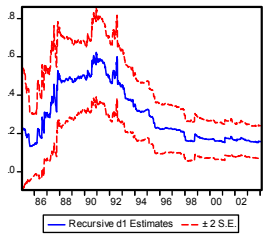

Volkswagen
Recursive c1 Estimates
± 2 S.E.

JAPAN

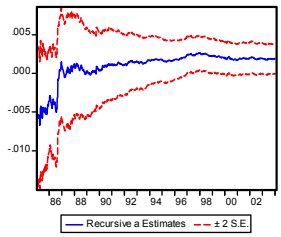
NIKKEI 225



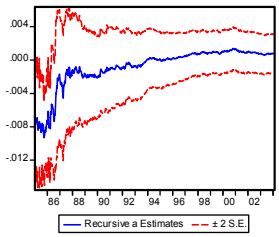
NIKKEI 225



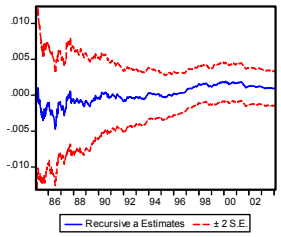
Toyota Motor Corp



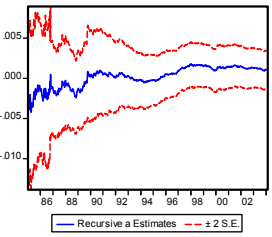
Matsushita Electric INDL



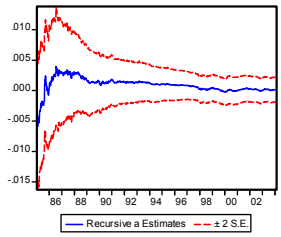
SONY



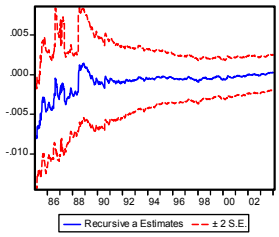
Fuji Photo Films



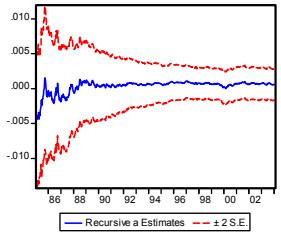
SAPPORO HDG



Nippon Steel



Mitsubishi HeavyIndustries



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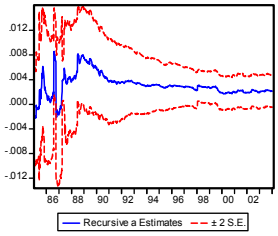

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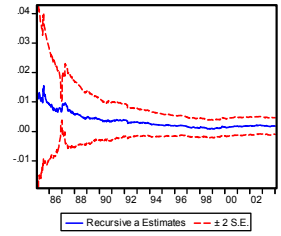
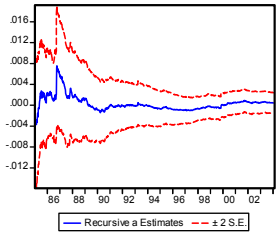


Tokyo Electric Power



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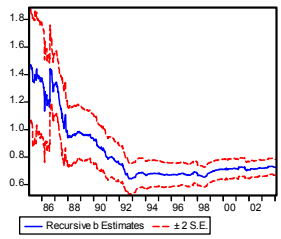

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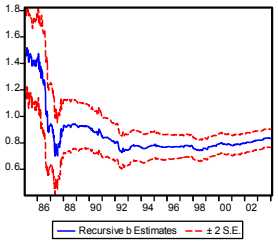
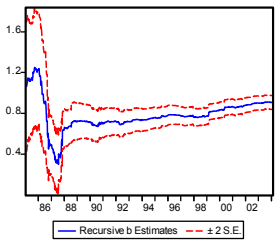
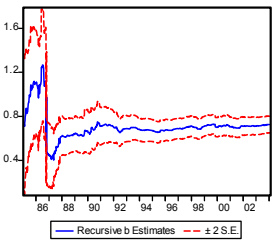


SONY



Fuji Photo Films



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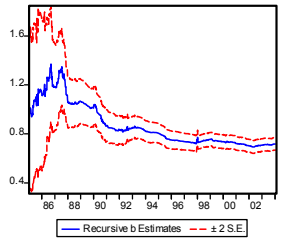
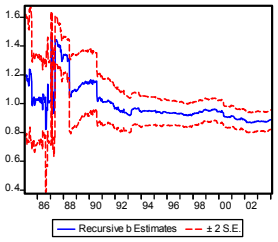
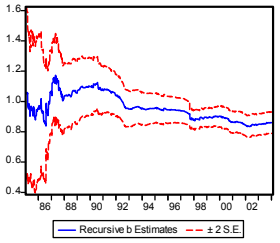


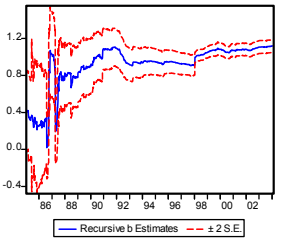
Nippon Steel



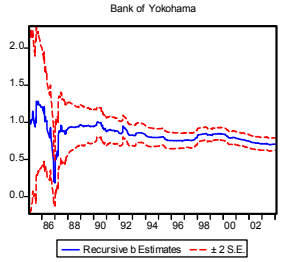
Mitsubishi Heavy Industries



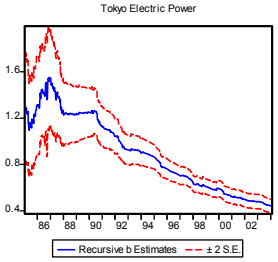
Kawasaki Heavy Industries

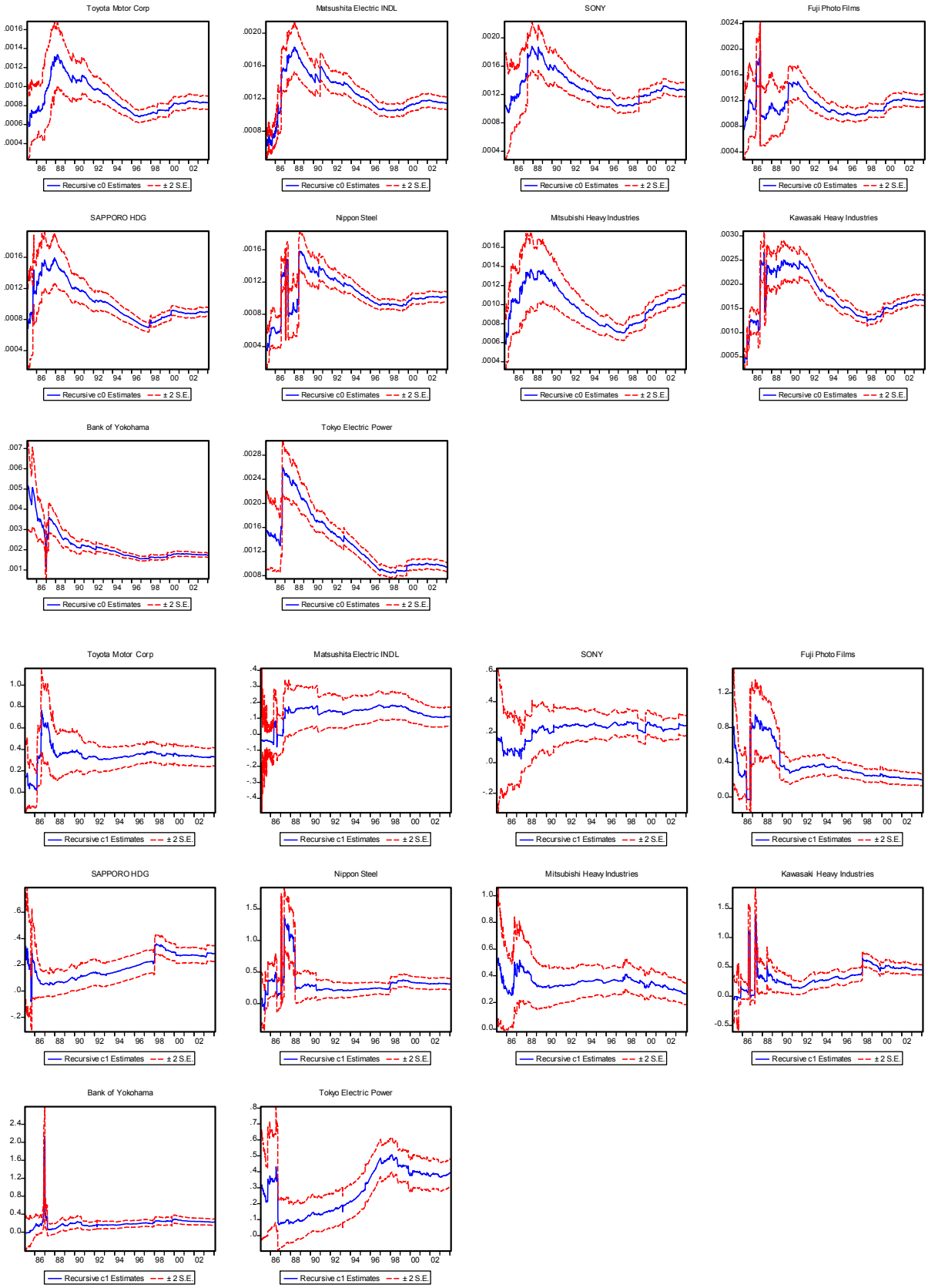


Bank of Yokohama



Tokyo Electric Power

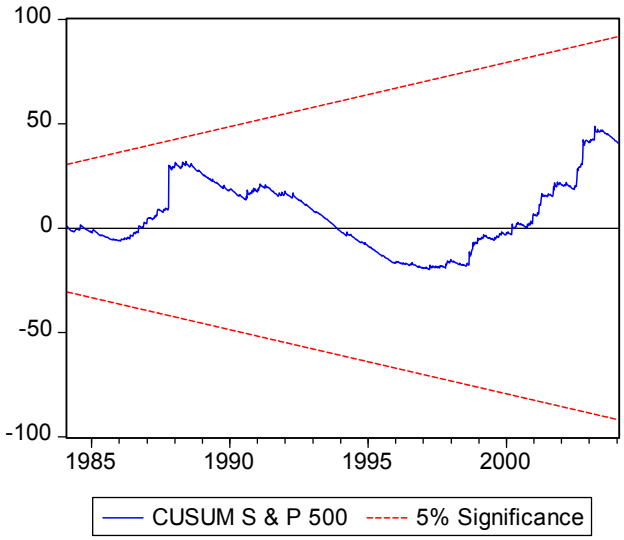


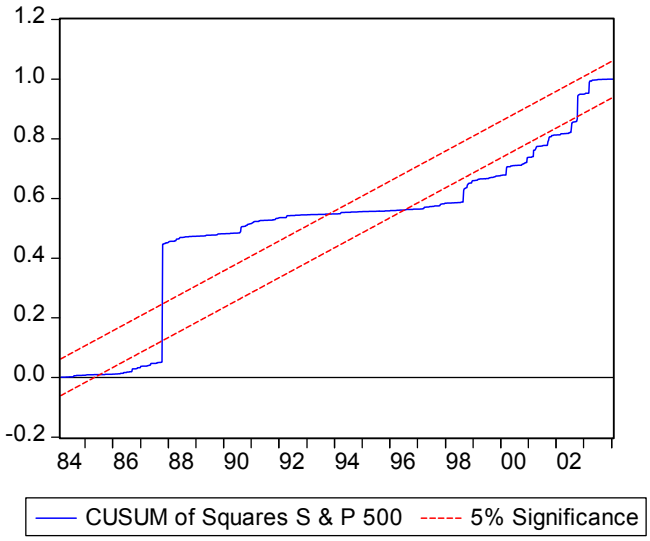

Toyota Motor Corp
Matsushita Electric INDL
SONY
Fuji Photo Films
SAPPORO HDG
Nippon Steel
Mitsubishi Heavy Industries
Kawasaki Heavy Industries
Bank of Yokohama
Tokyo Electric Power
Recursive c0 Estimates
± 2 S.E.
Toyota Motor Corp
Matsushita Electric INDL
SONY
Fuji Photo Films
SAPPORO HDG
Nippon Steel
Mitsubishi Heavy Industries
Kawasaki Heavy Industries
Bank of Yokohama
Tokyo Electric Power
Recursive c1 Estimates
± 2 S.E.

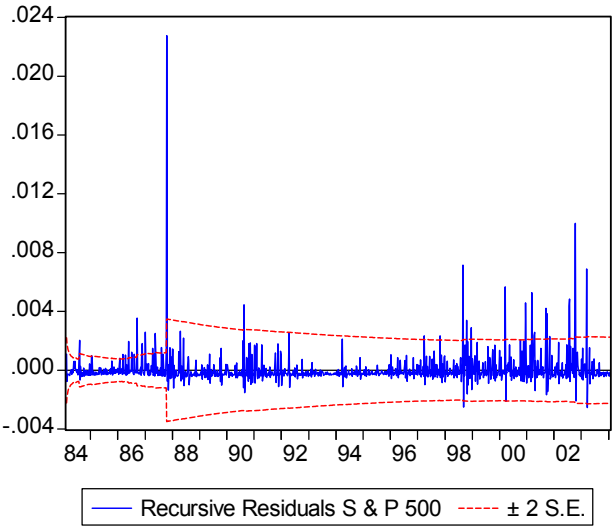
3) Recursive residuals, CUSUM, CUSUM of SQUARES and one-step forecast tests in the parameters d_0 , d_1 of the market index and c_0 , c_1 of the stocks.

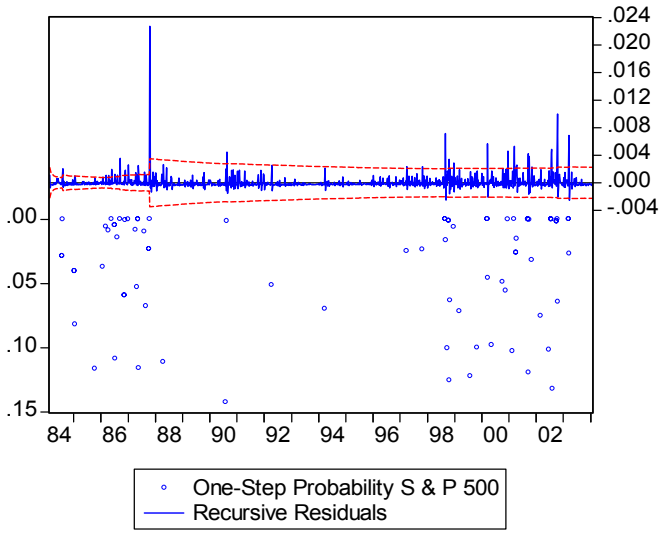
U.S.A

S&P 500:

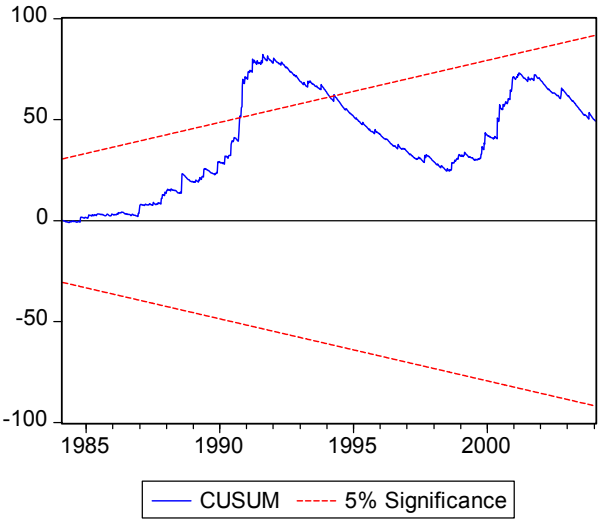


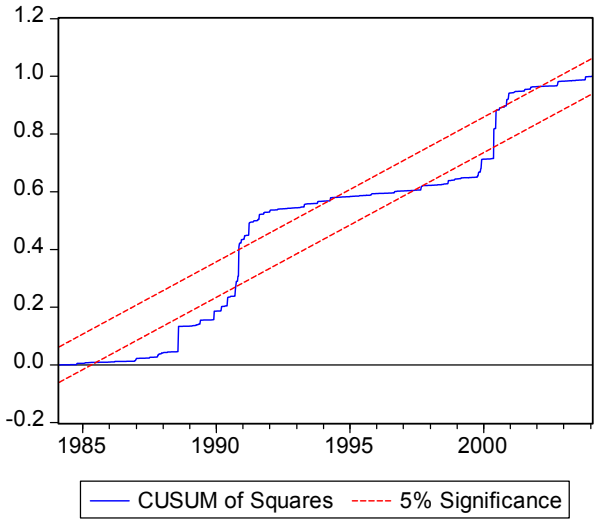


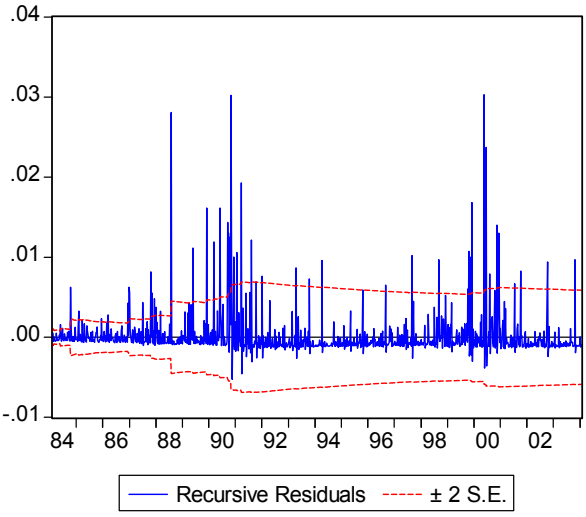


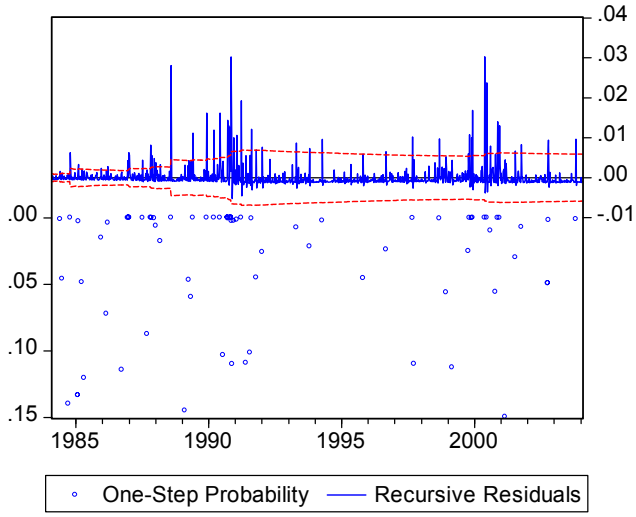


Bank of America:

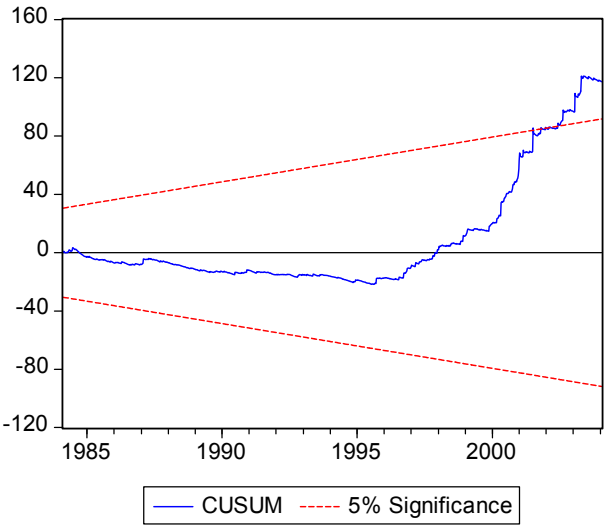


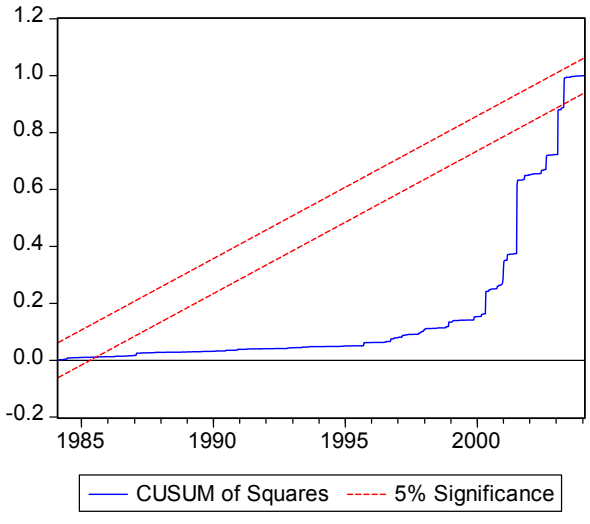


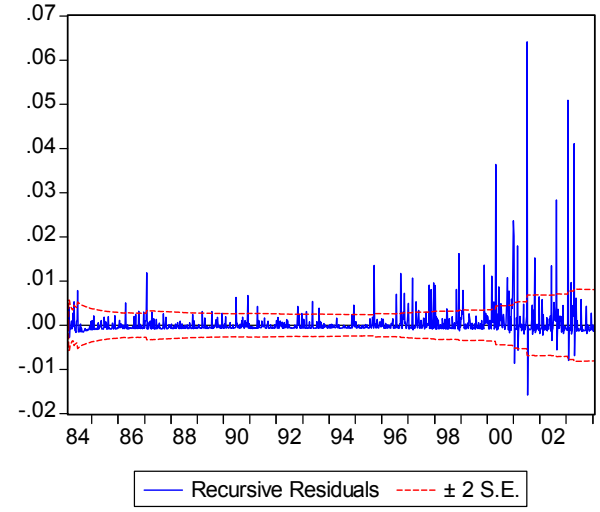




AT & T:



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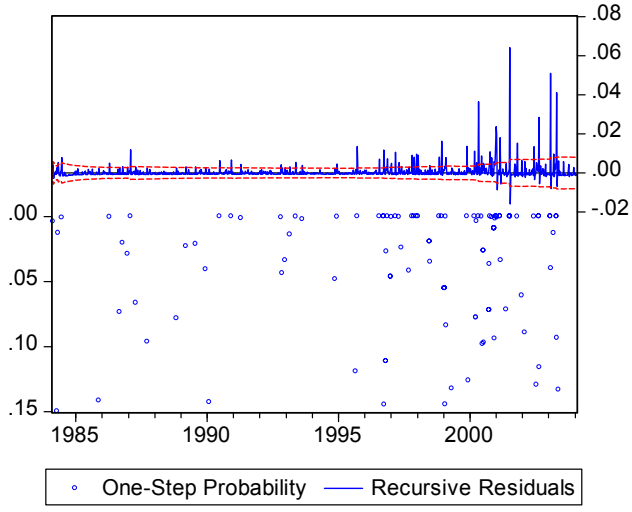
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.


.08
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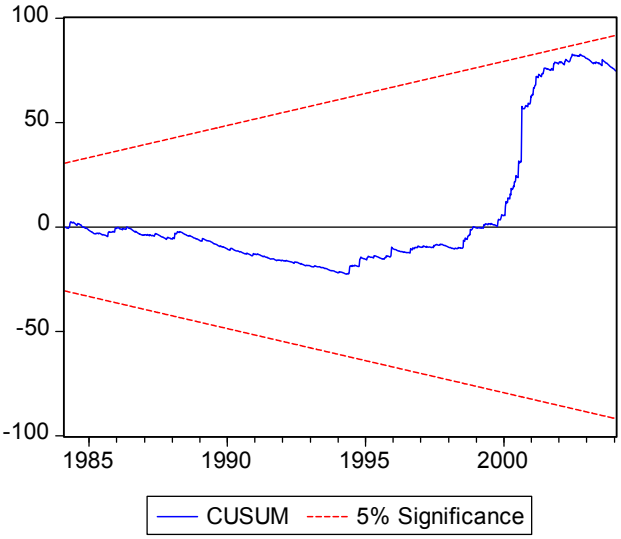
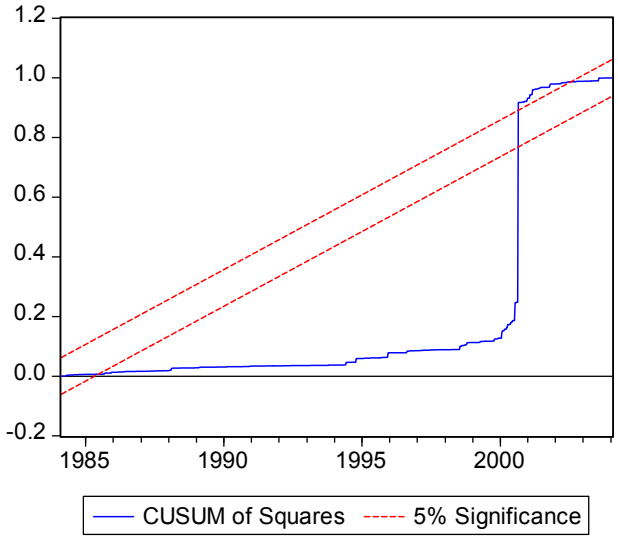
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Bausch & Lomb:


100
50
0
-50
-100
1985 1990 1995 2000
CUSUM
5% Significance


1.2
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0.8
0.6
0.4
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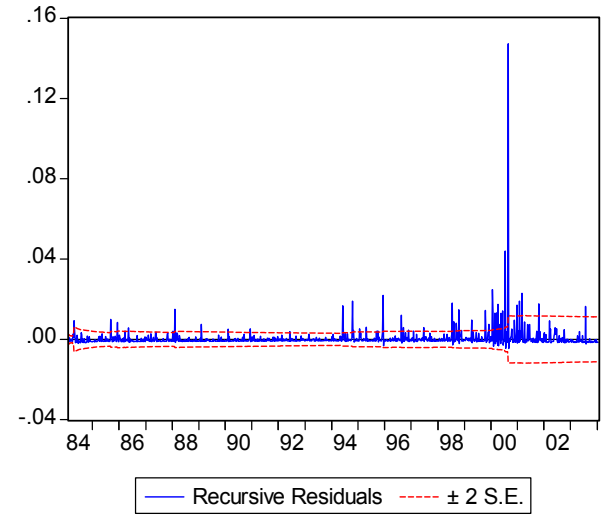
0.0
-0.2
1985 1990 1995 2000
CUSUM of Squares
5% Significance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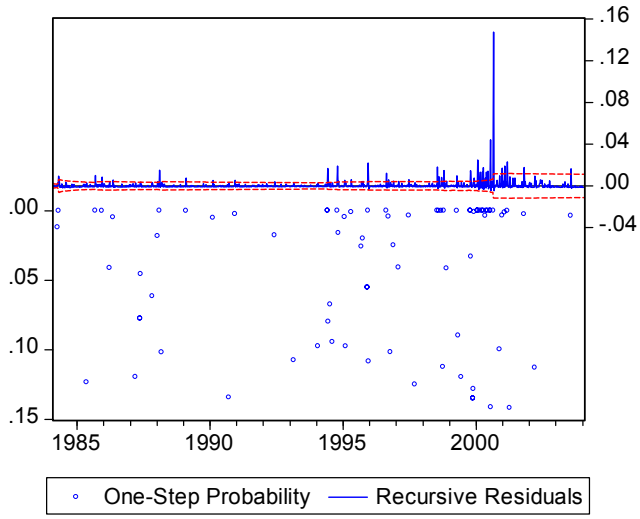
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.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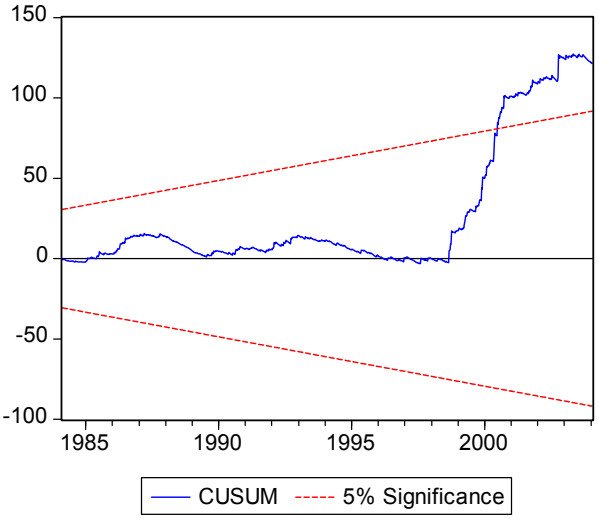
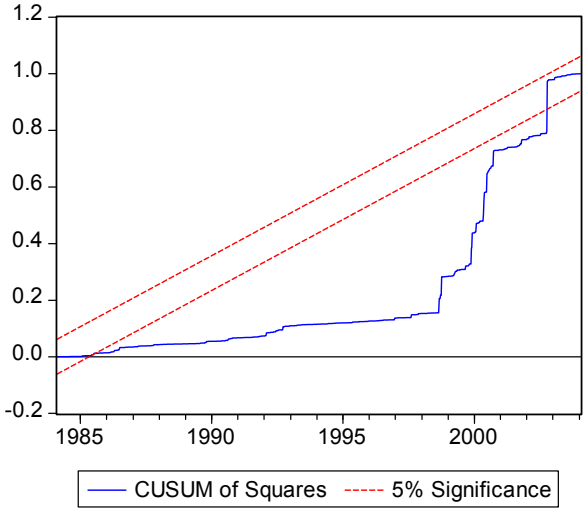
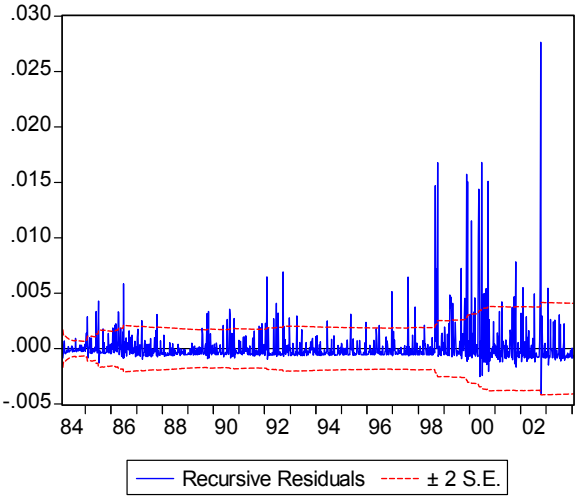
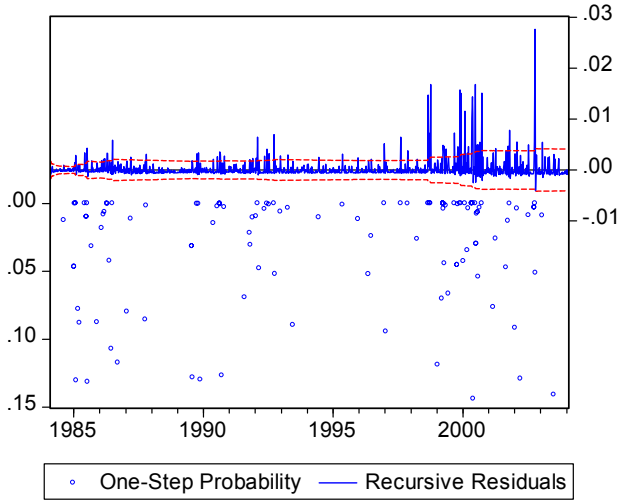
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Coca-Cola:









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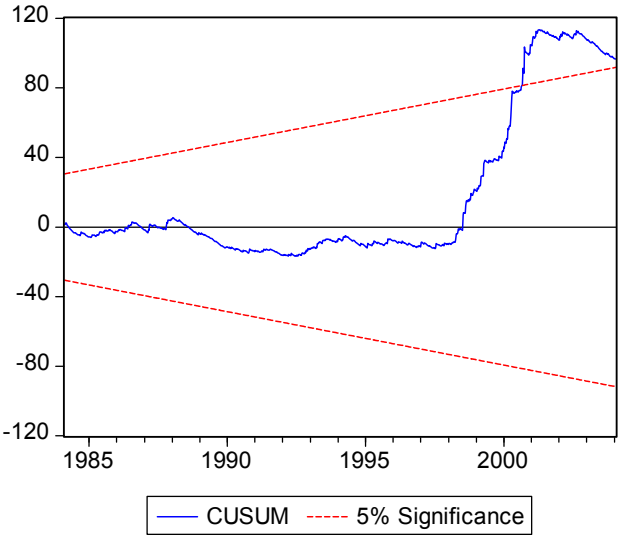

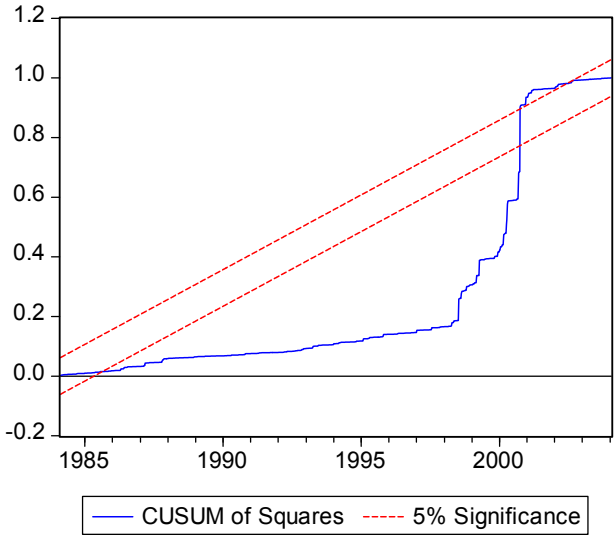

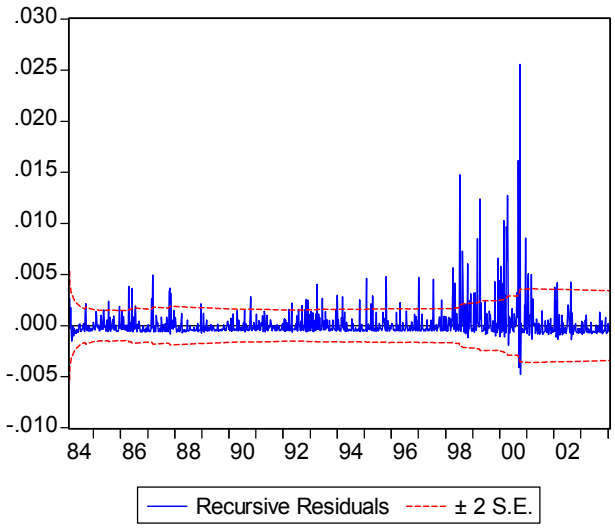
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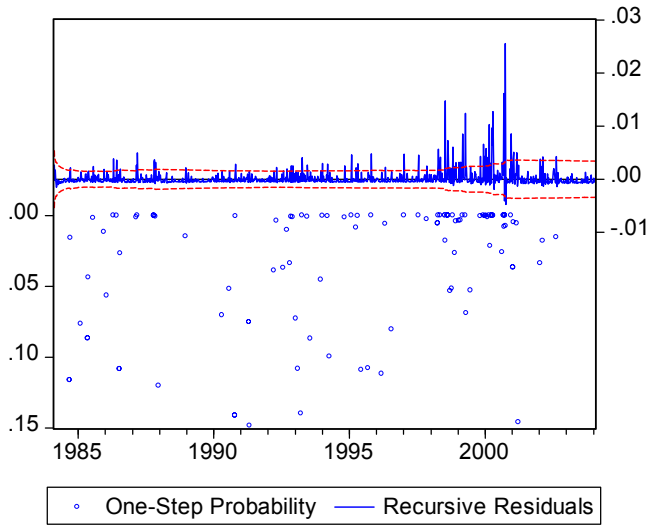
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.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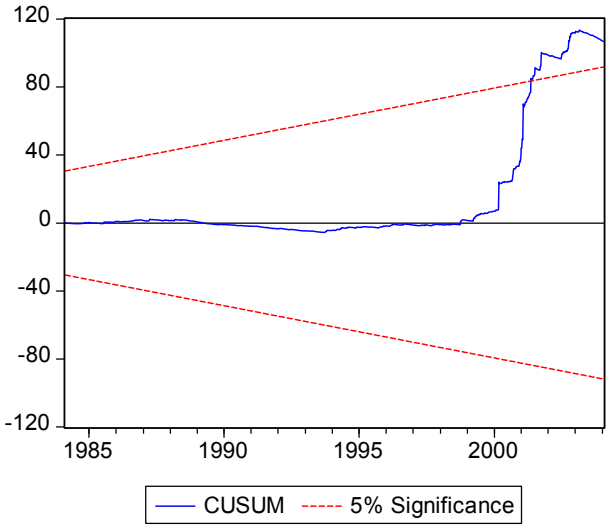
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Edison Intl: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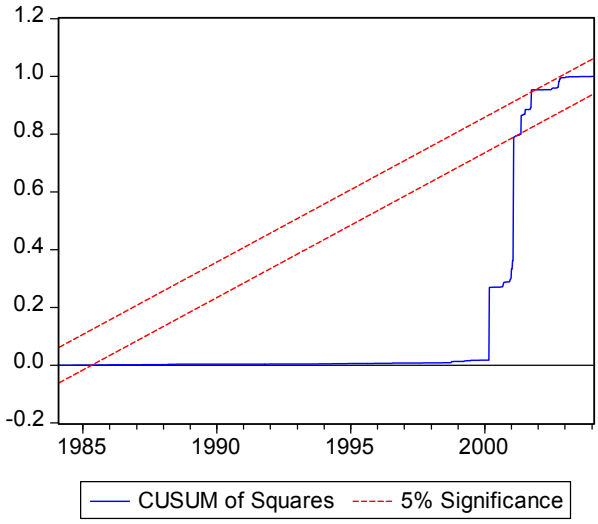
80
40
0
-40
-80
-120
1985 1990 1995 2000
CUSUM
5% Significance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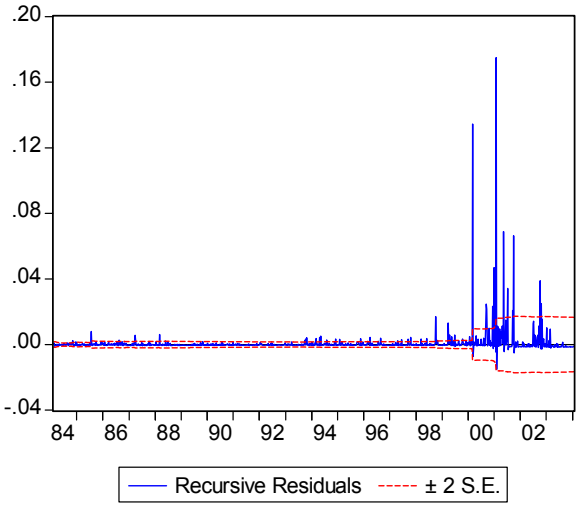
1985 1990 1995 2000
CUSUM of Squares
5% Significance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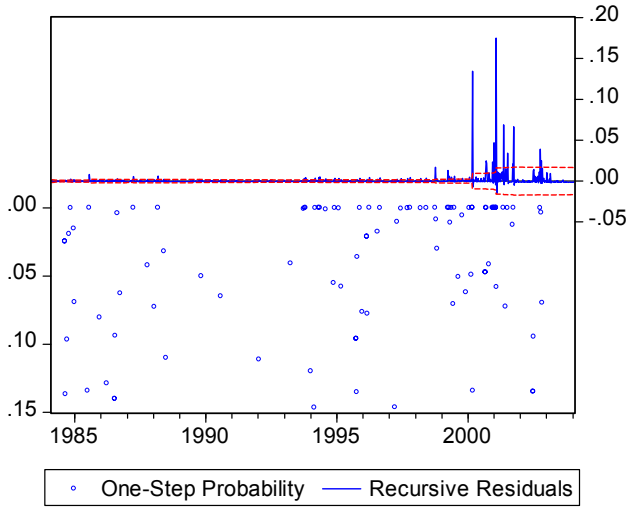
Recursive Residuals
± 2 S.E.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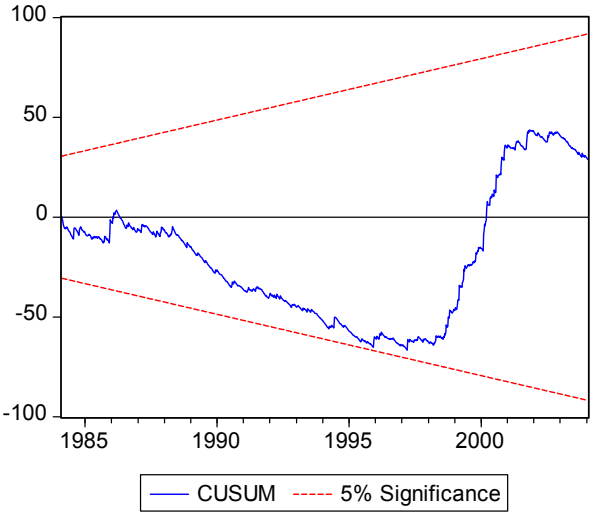
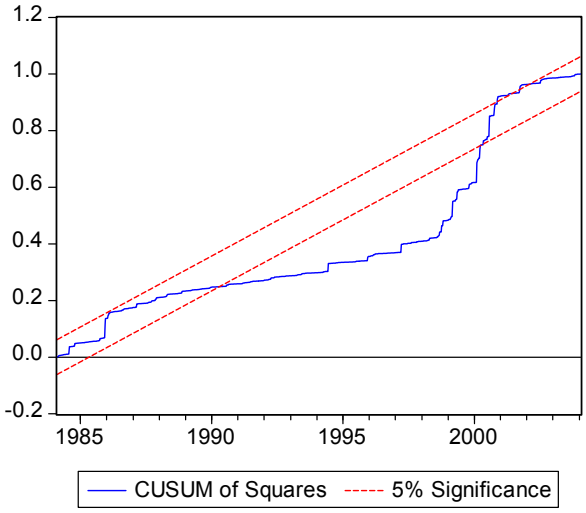
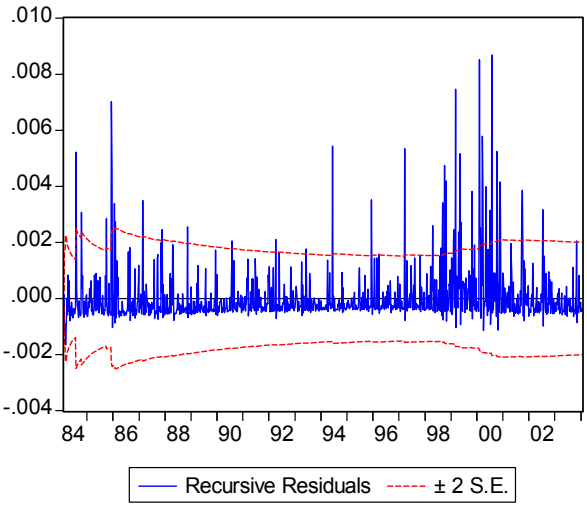
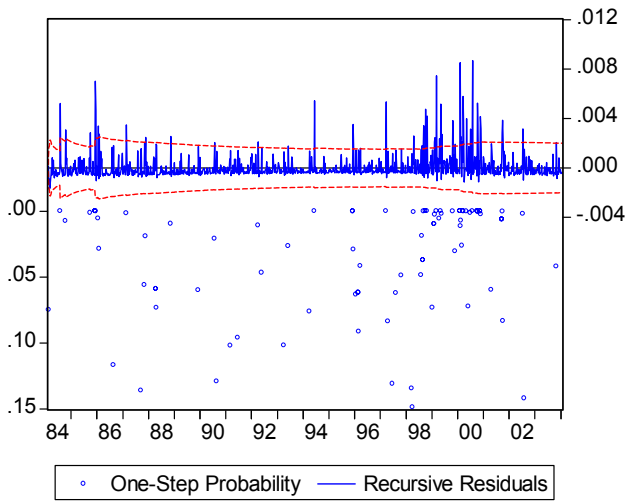
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Exxon-Mobil:









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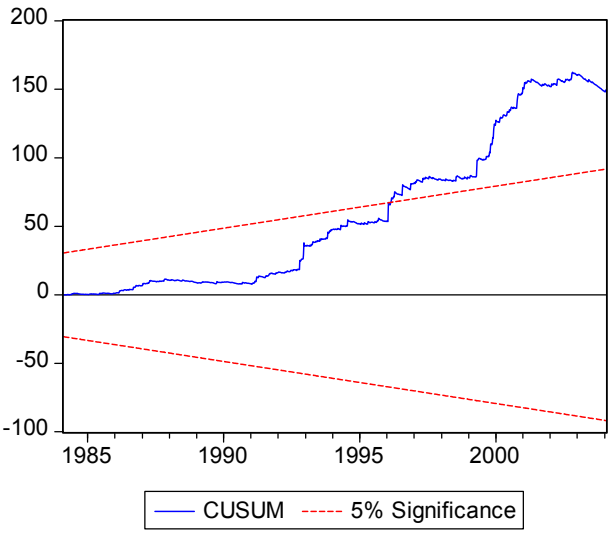

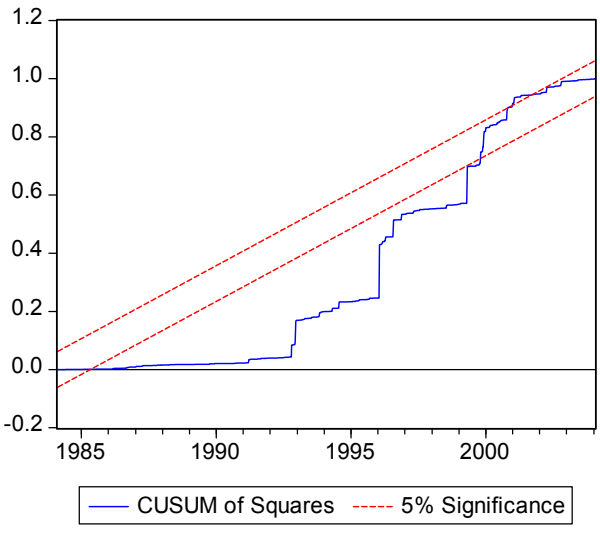

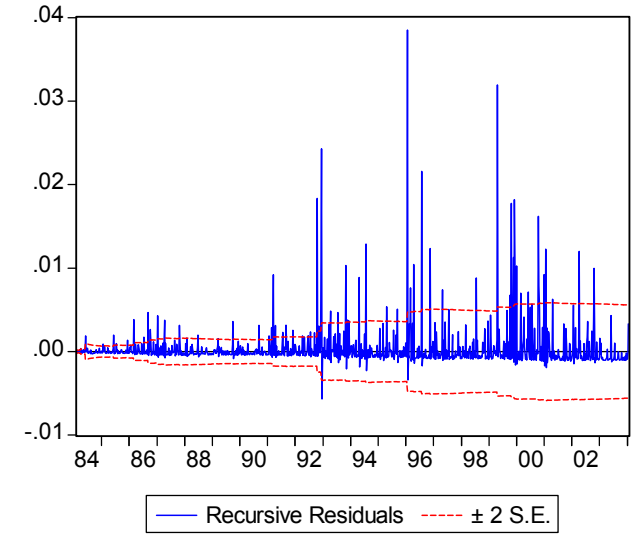
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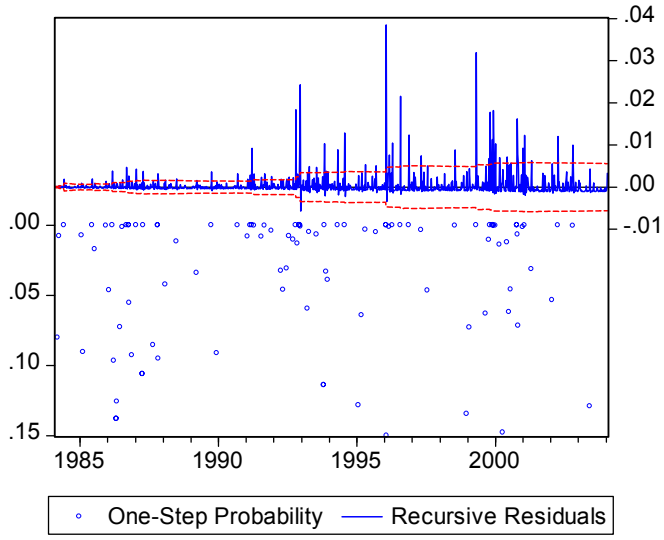
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.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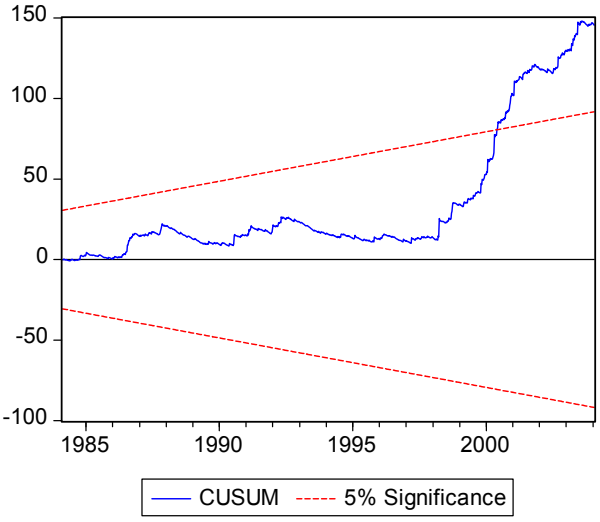
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Mc Donalds: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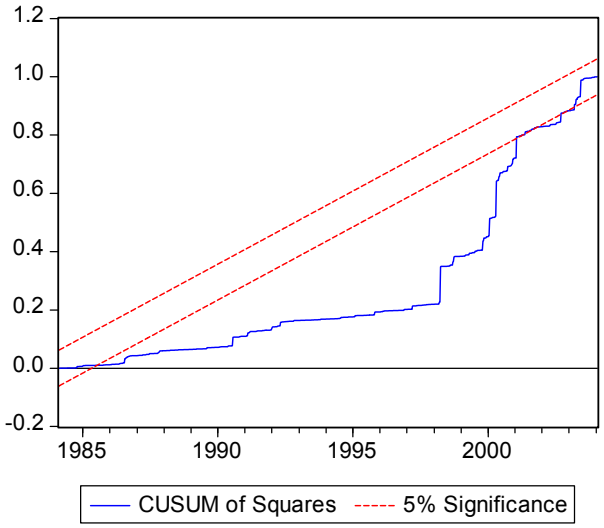
-50
-100
1985 1990 1995 2000
CUSUM
5% Significance


1.2
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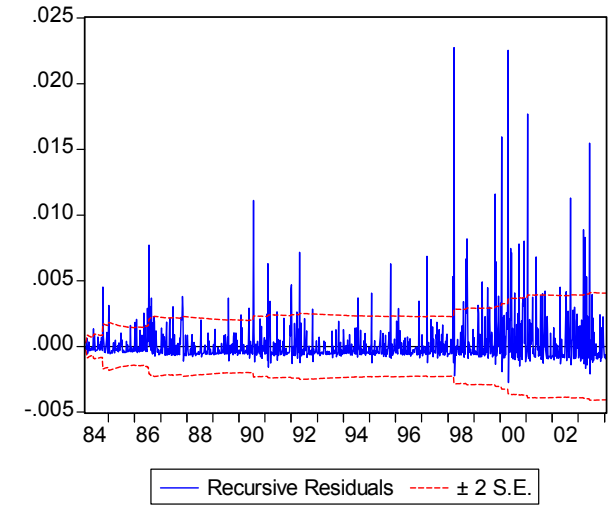
0.6
0.4
0.2
0.0
-0.2
1985 1990 1995 2000
CUSUM of Squares
5% Significance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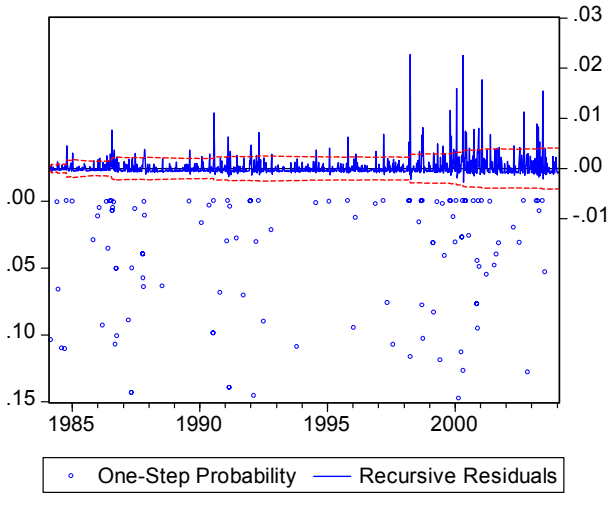
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.


.03
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.05
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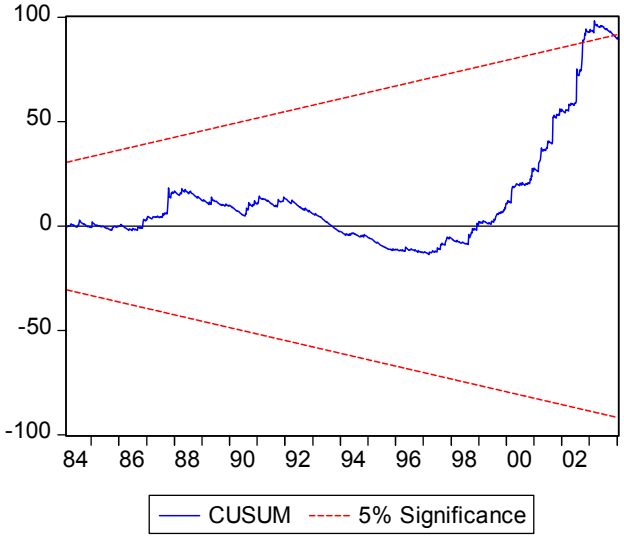
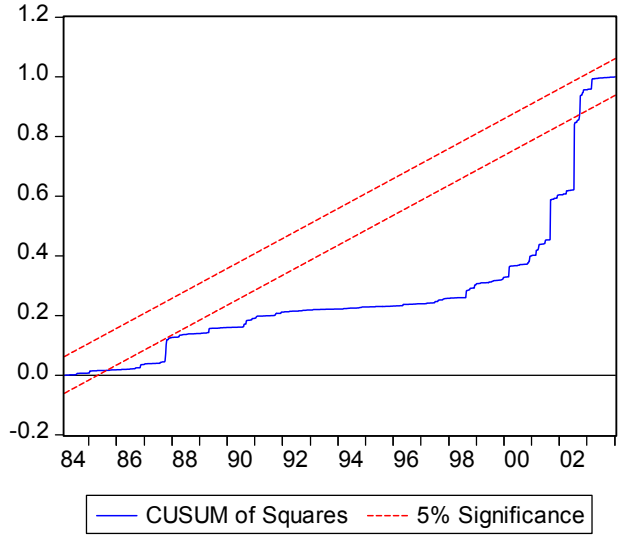
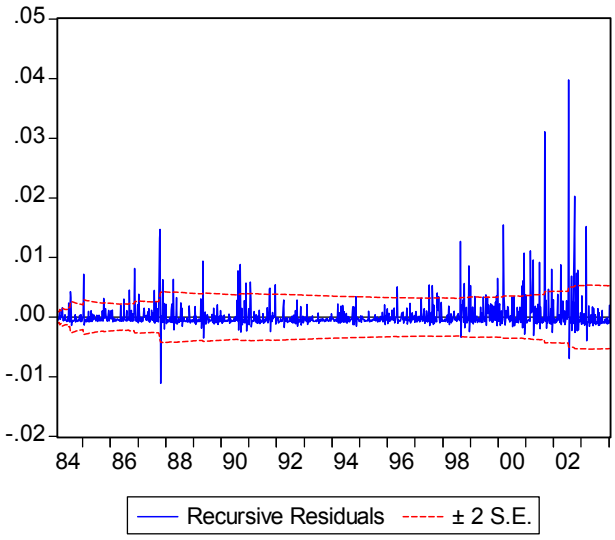
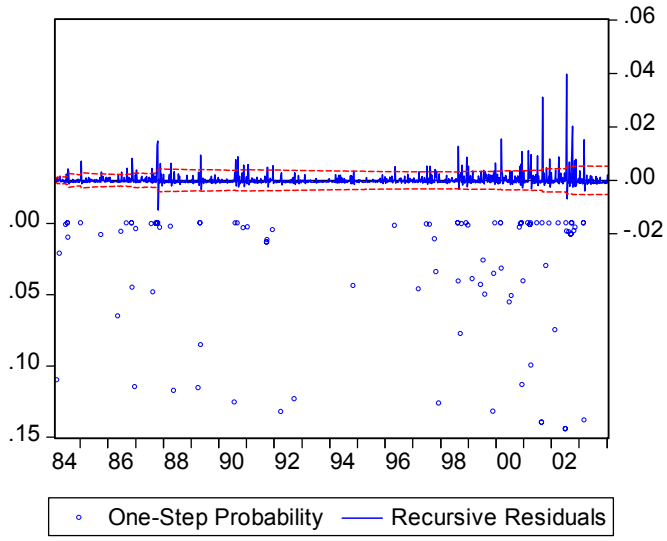
.15
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

General Electric:



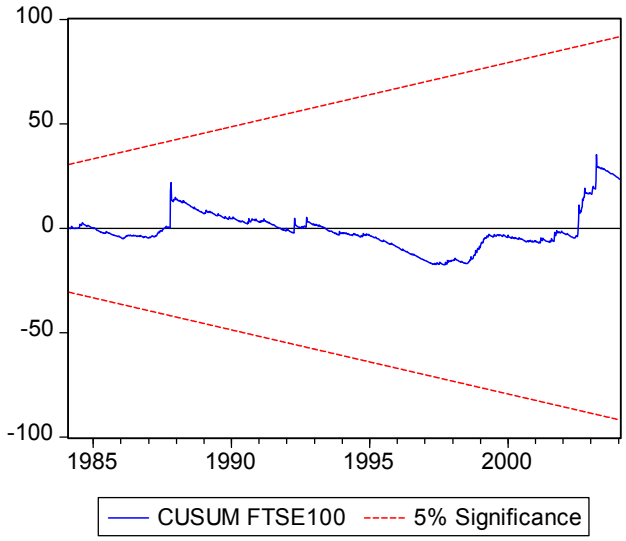






U.K.

FTSE100:


100
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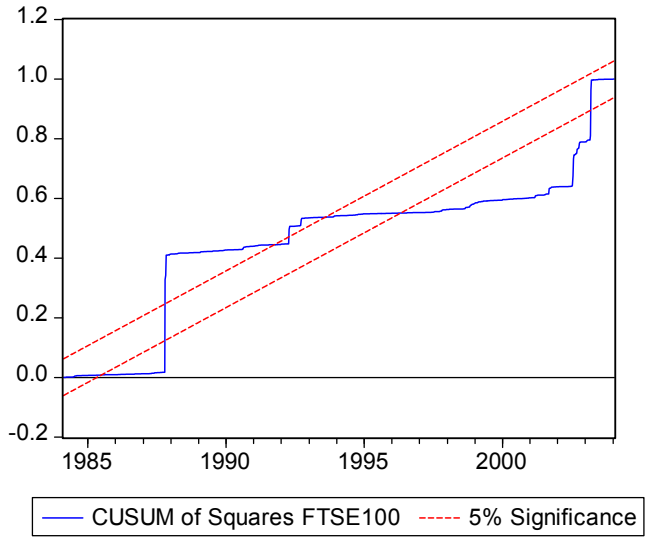
0
-50
-100
1985
1990
1995
2000
CUSUM FTSE100
5% Significance


1.2
1.0
0.8
0.6
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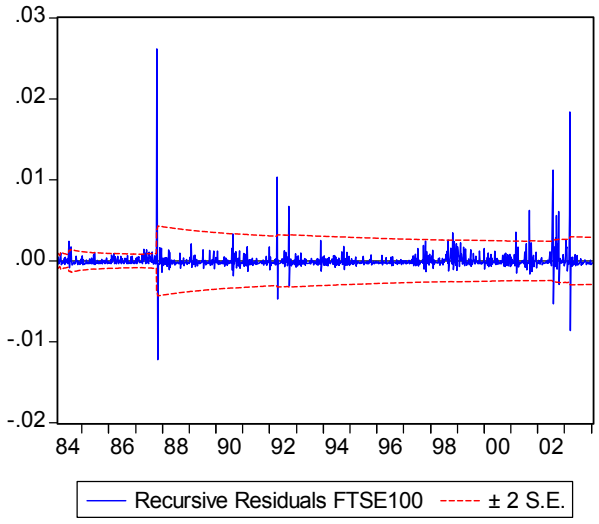
0.2
0.0
-0.2
1985
1990
1995
2000
CUSUM of Squares FTSE100
5% Significance


.03
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84
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92
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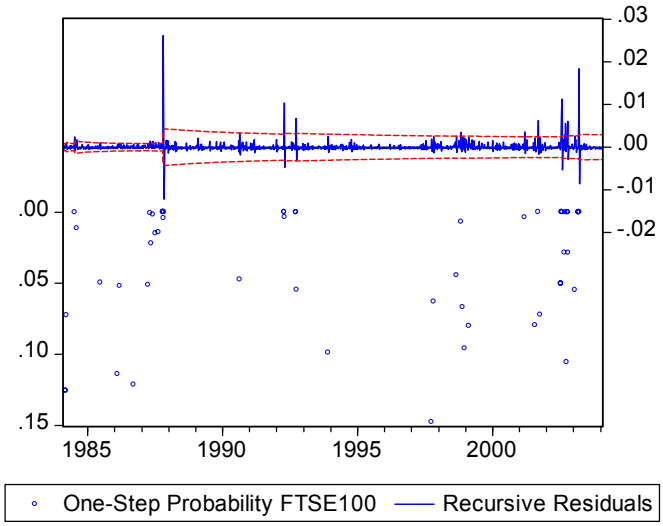
Recursive Residuals FTSE100
± 2 S.E.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1985
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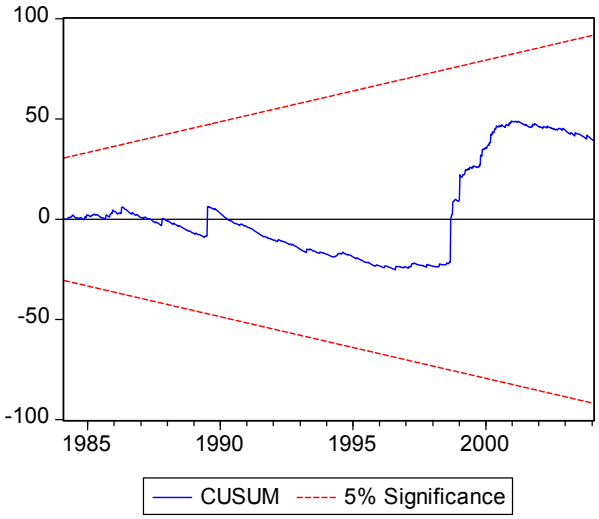
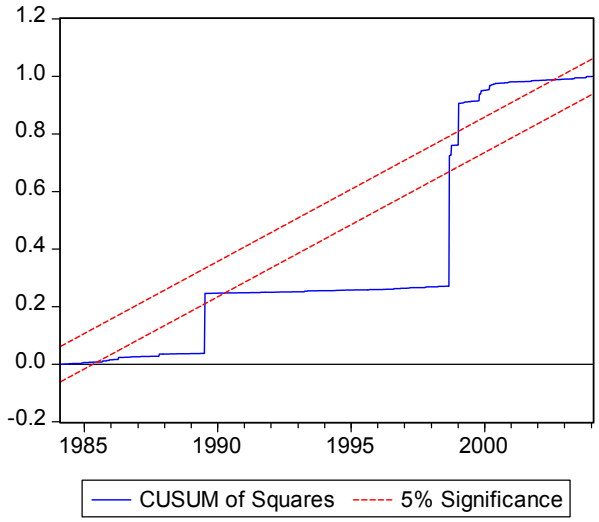
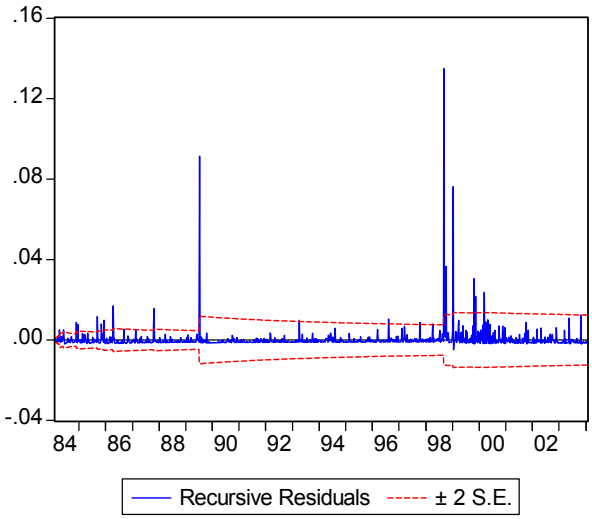
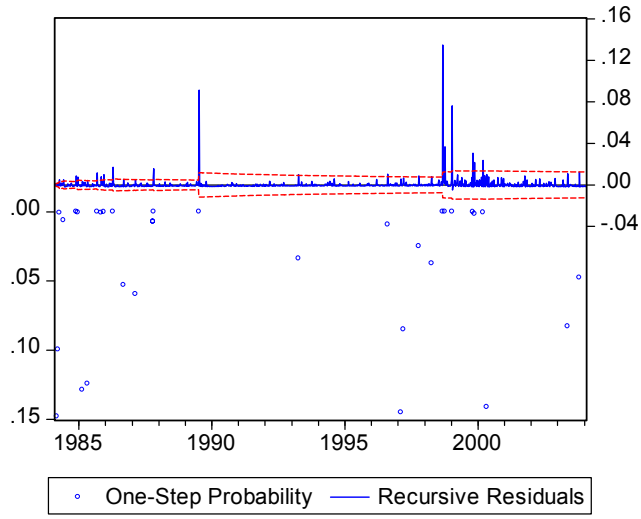
1995
2000
One-Step Probability FTSE100
Recursive Residuals

British American Tobacco:

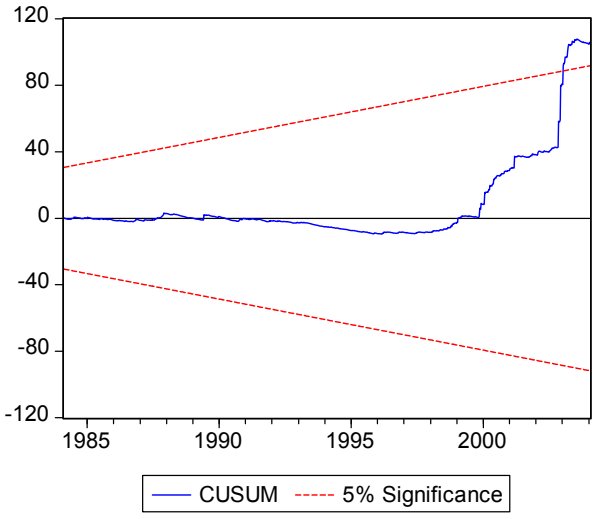


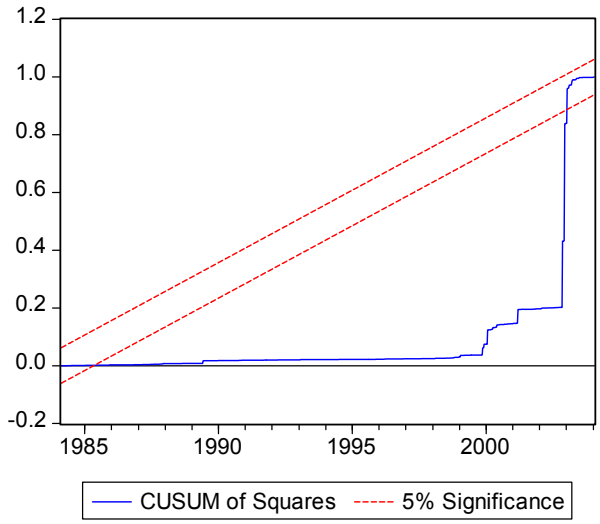


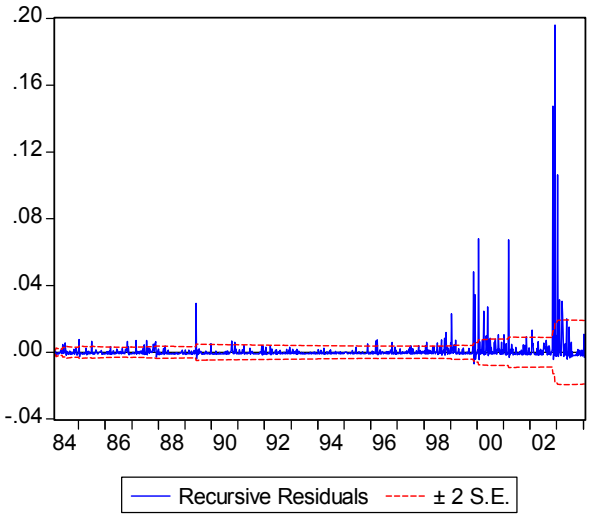


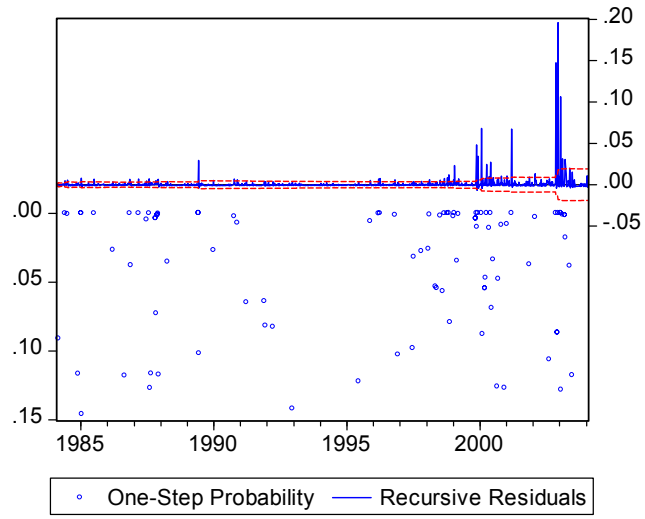


Cable & Wireless:

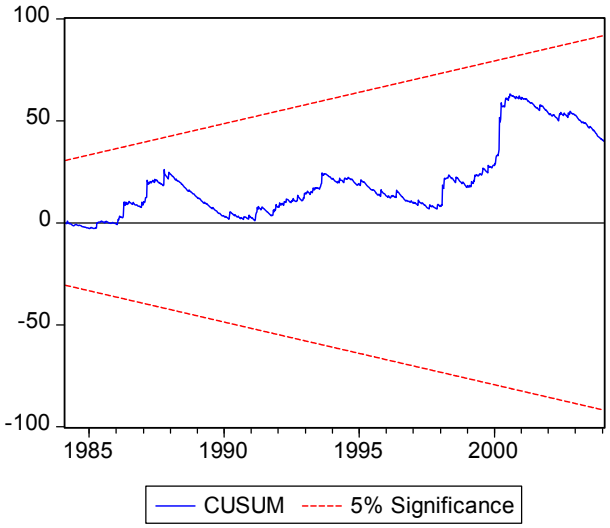


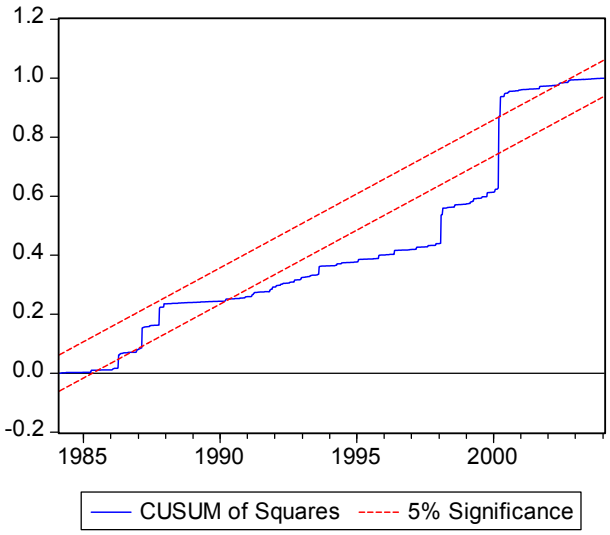


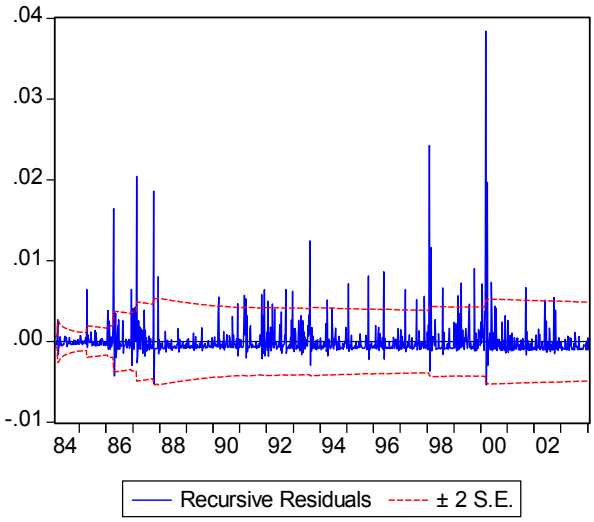


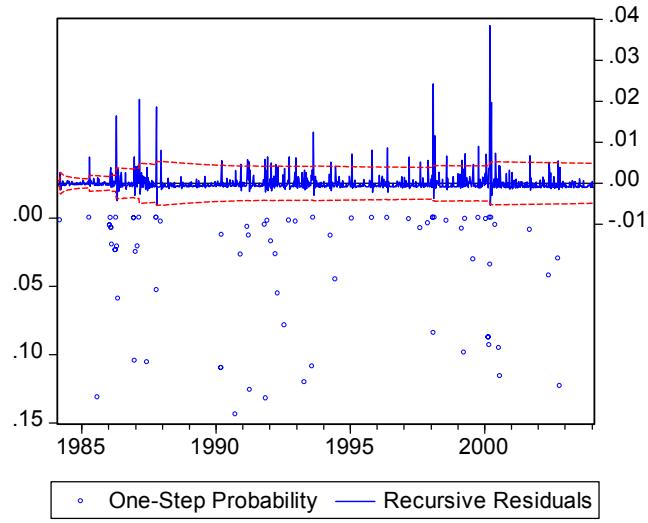


Glaxo Smith Kline:

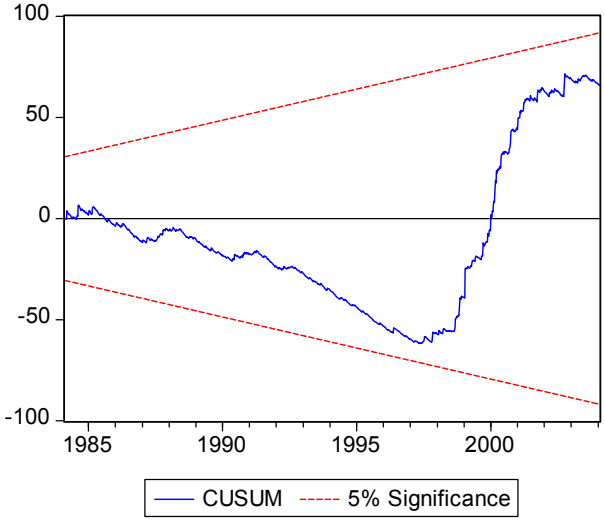


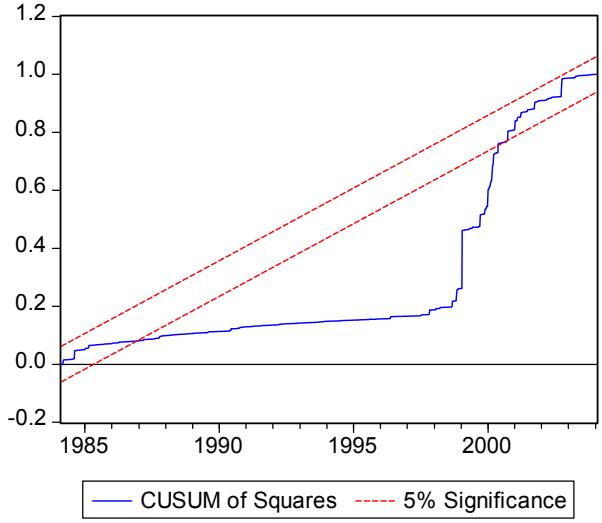


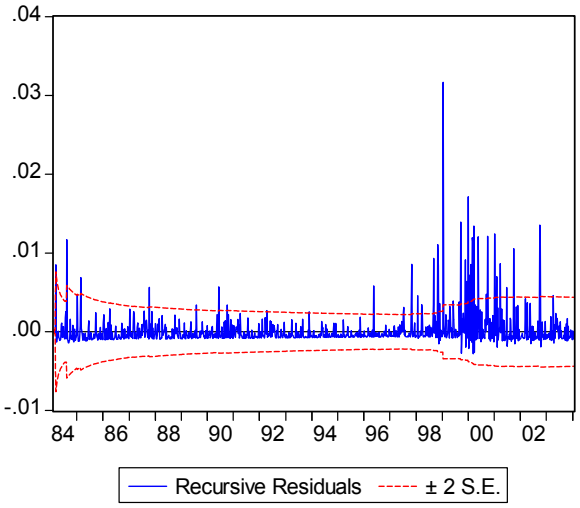


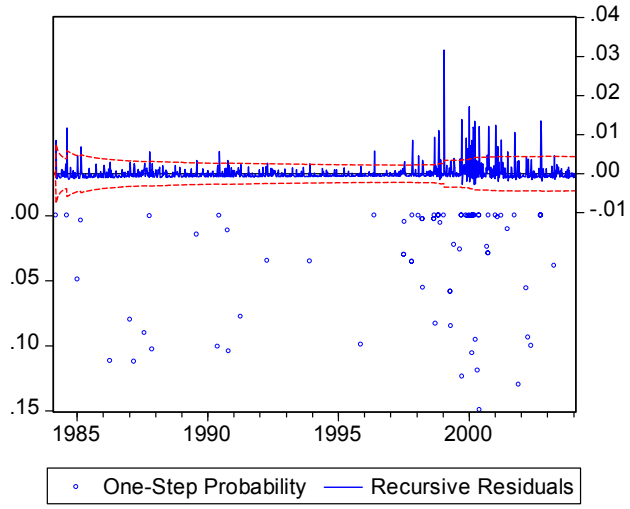


Marks & Spencer Group:

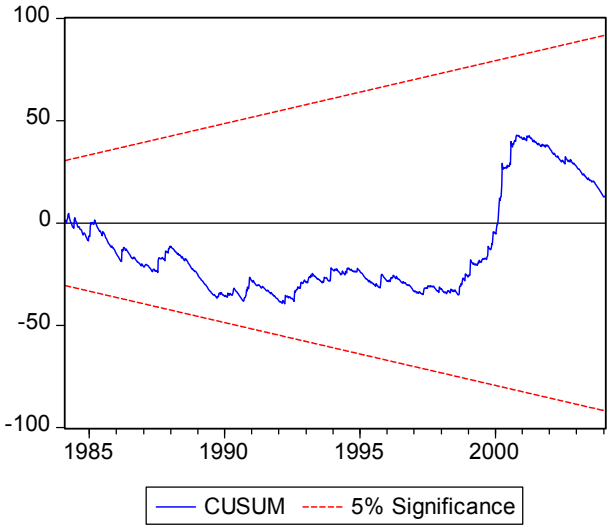


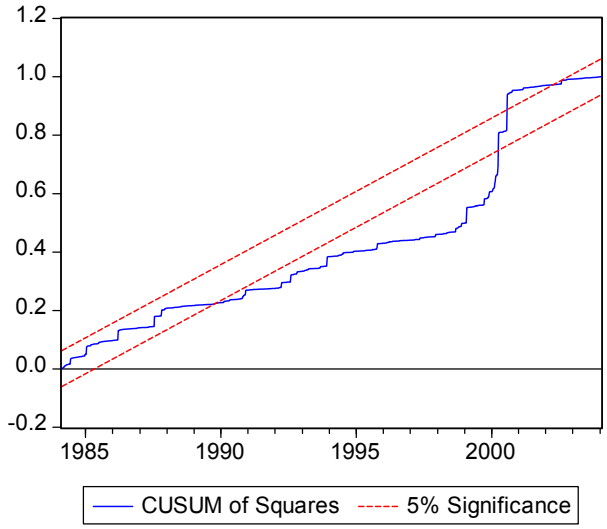


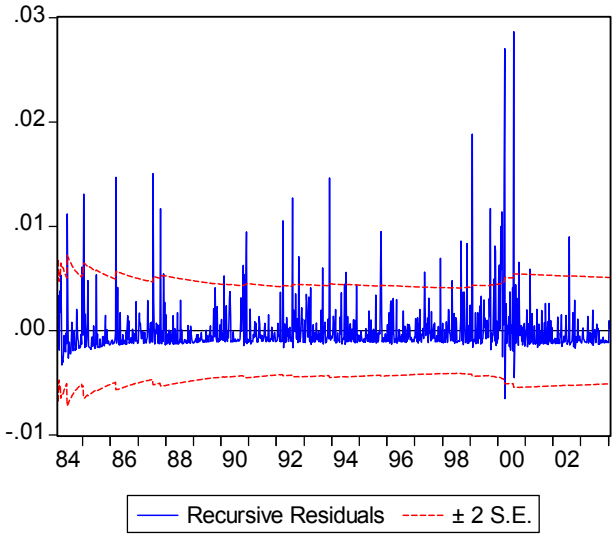




Royal Bank of Scotland:






.03
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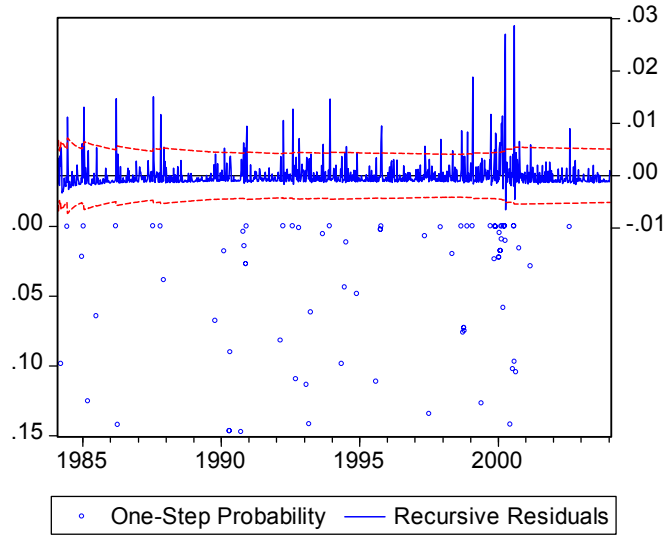
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.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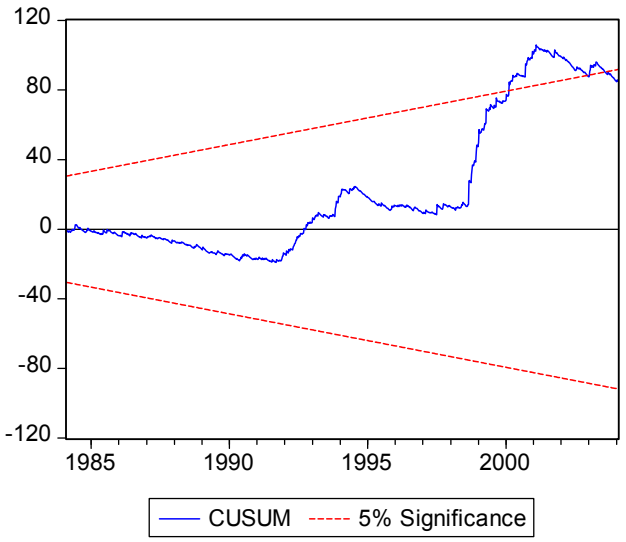
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Tesco: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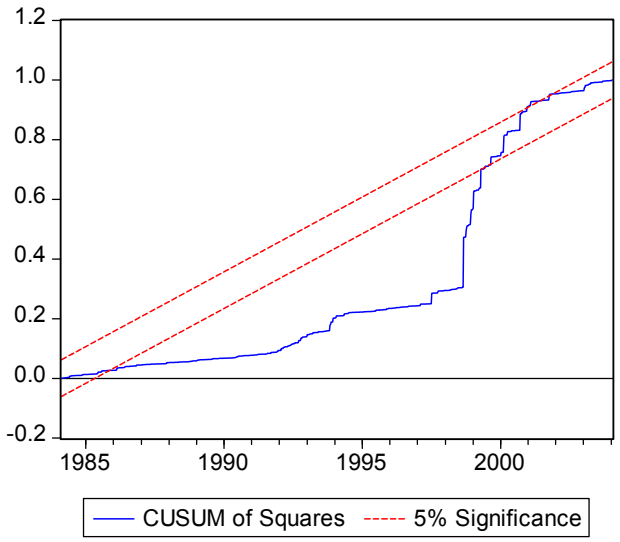
-40
-80
-120
1985 1990 1995 2000
CUSUM
5% Significance


1.2
1.0
0.8
0.6
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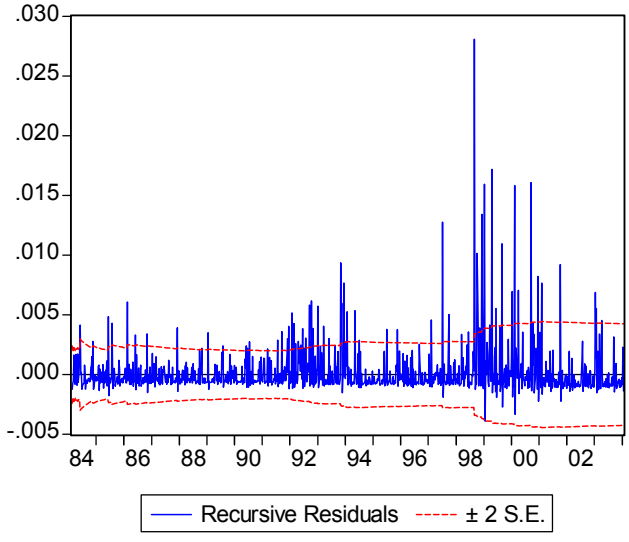
0.0
-0.2
1985 1990 1995 2000
CUSUM of Squares
5% Significance


.030
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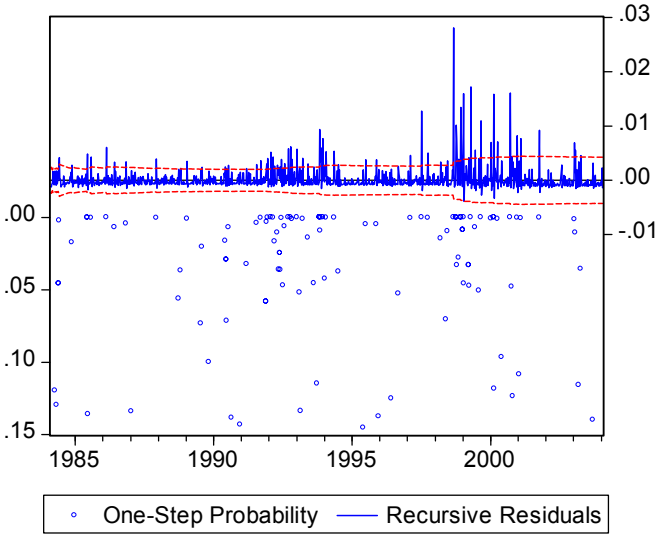
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.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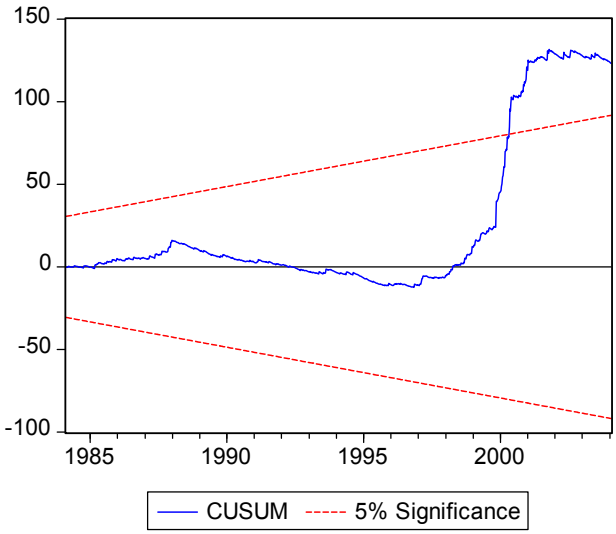
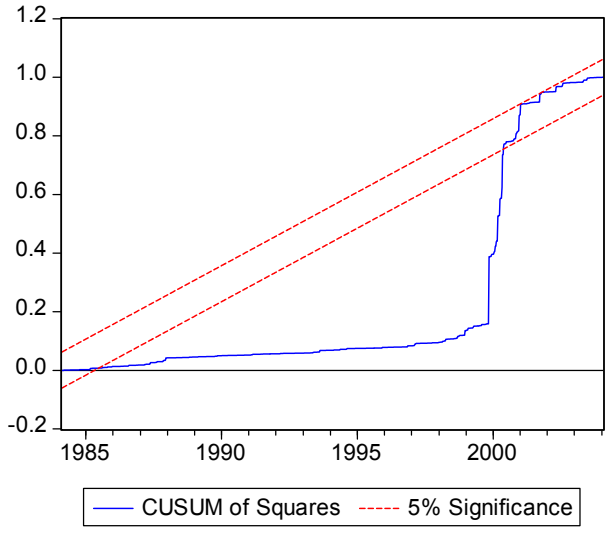
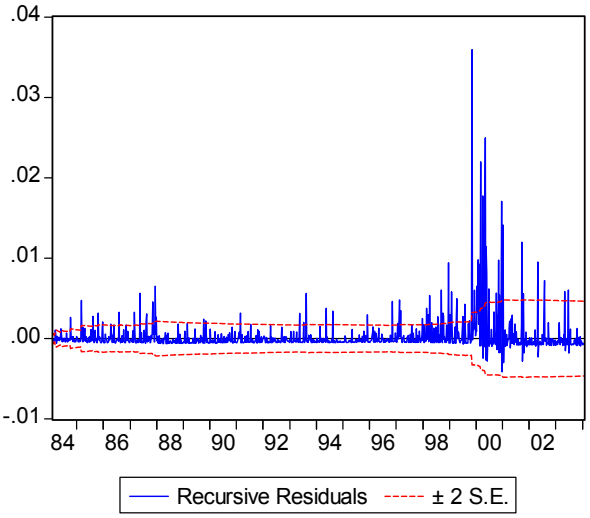
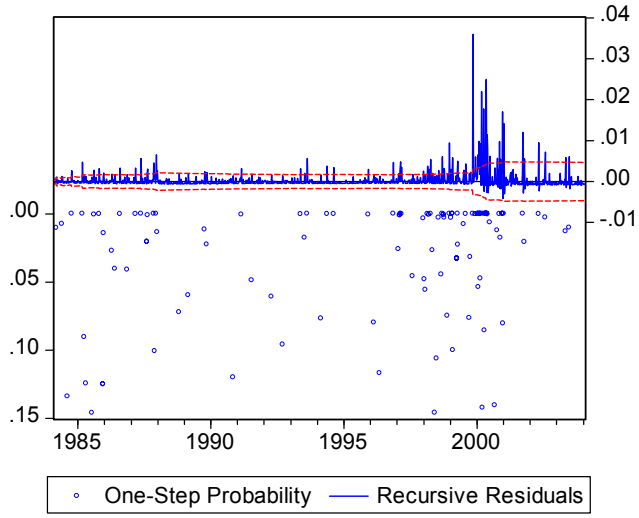
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Unilever:

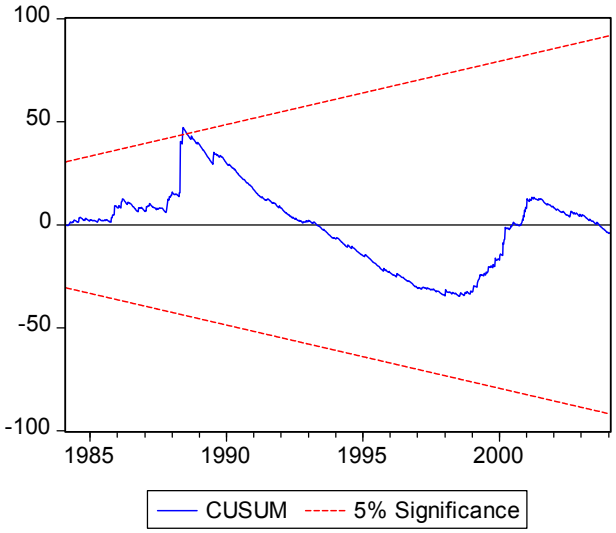


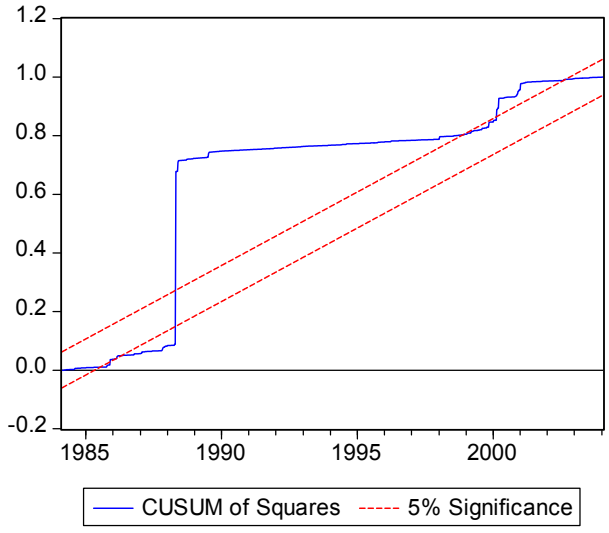


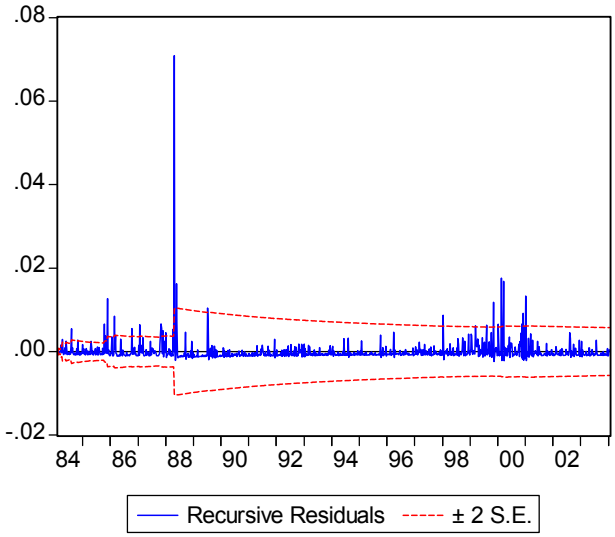


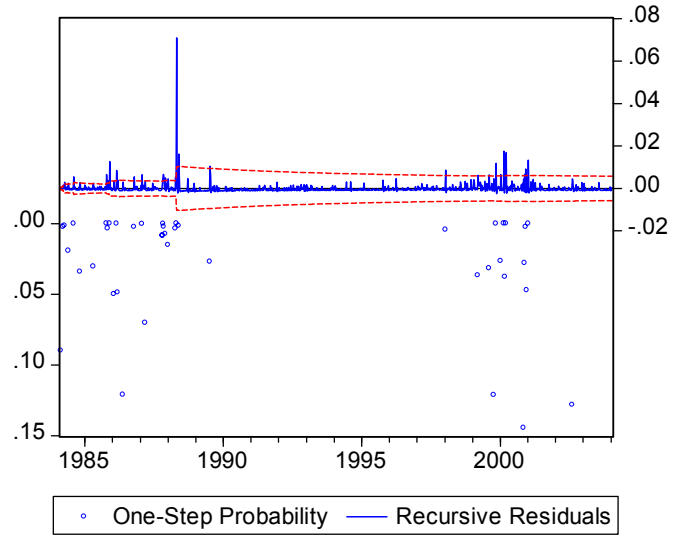


Cadburry Scheweppes:

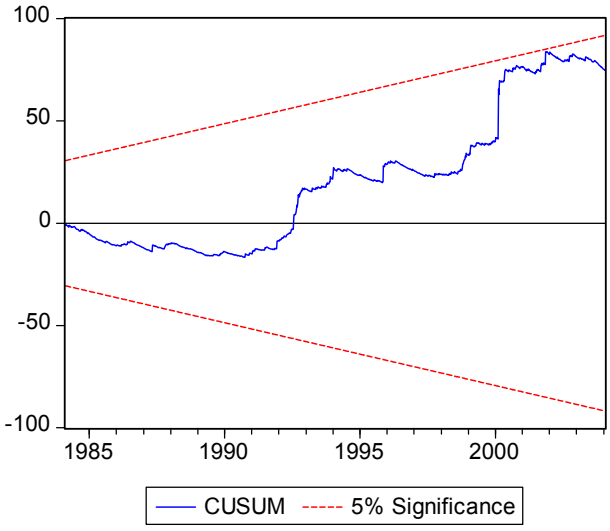


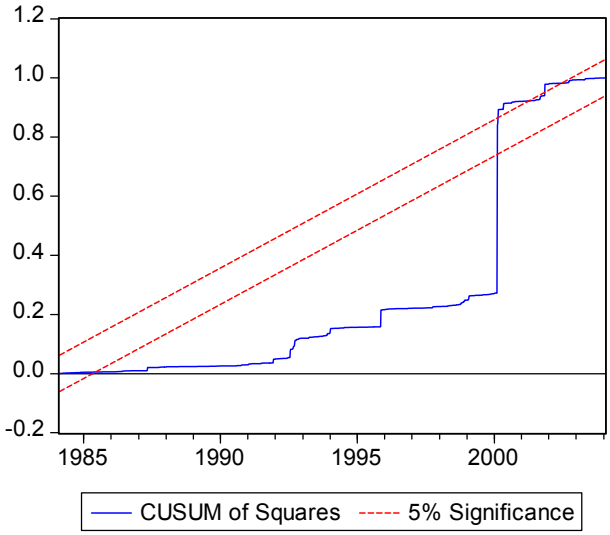


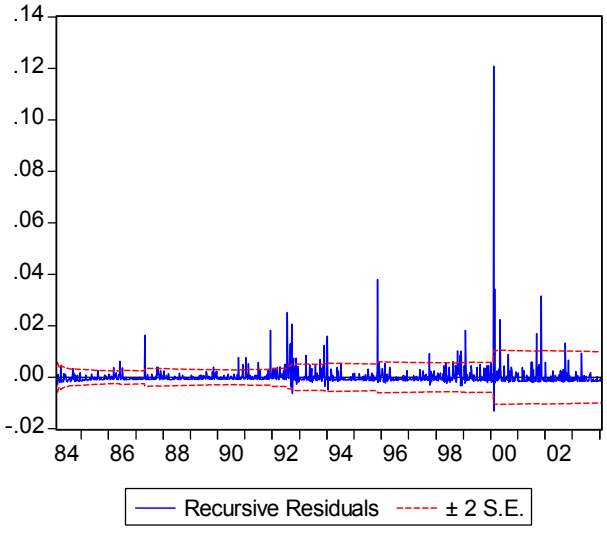


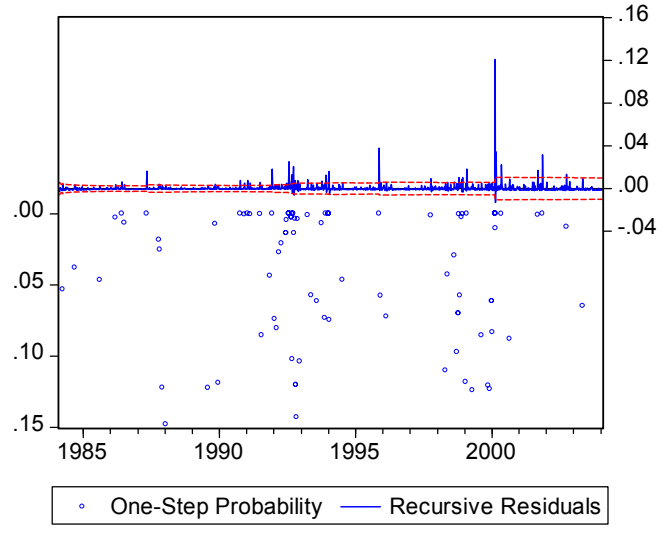


Hilton Group:

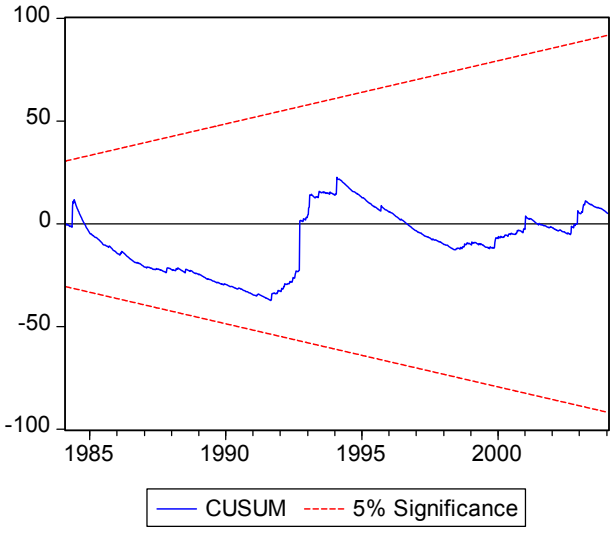








BAE Systems: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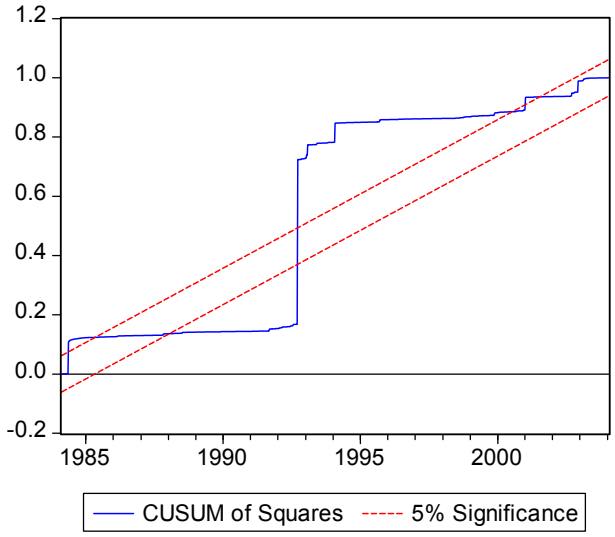
-100
1985
1990
1995
2000
CUSUM
5% Significance


1.2
1.0
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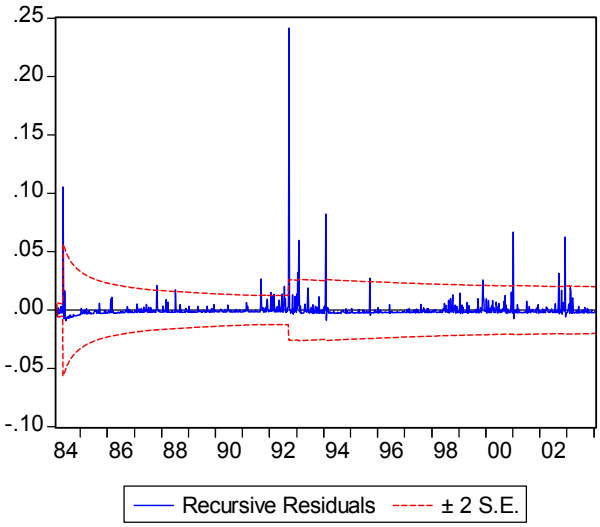
0.6
0.4
0.2
0.0
-0.2
1985
1990
1995
2000
CUSUM of Squares
5% Significance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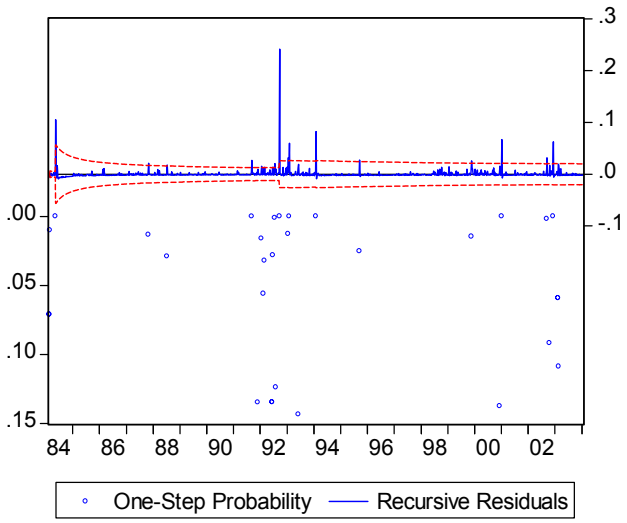
Recursive Residuals
± 2 S.E.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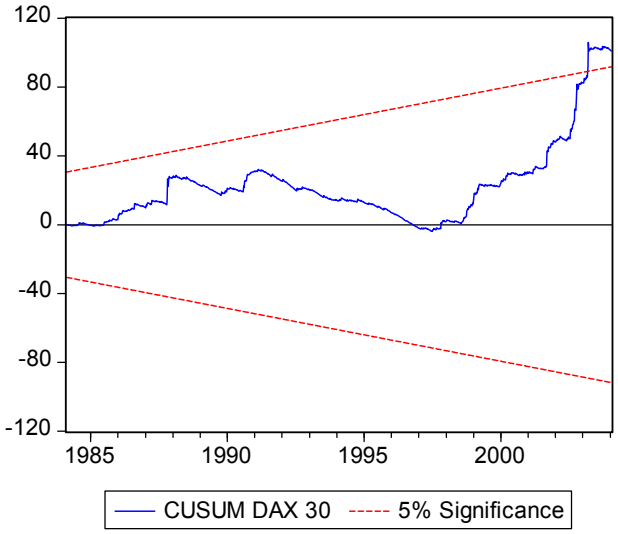
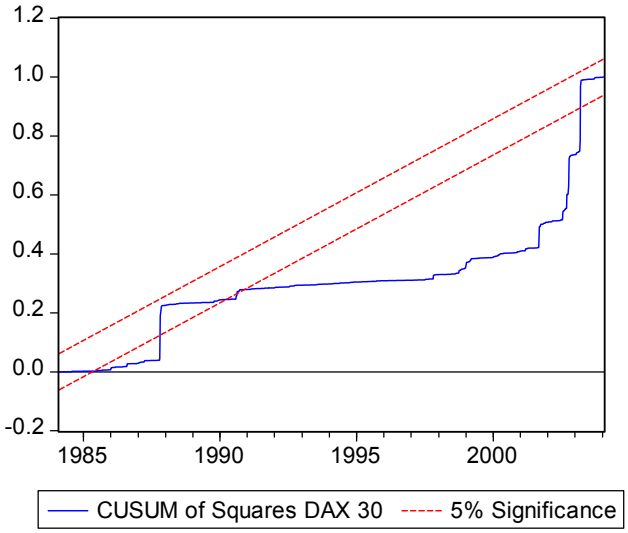
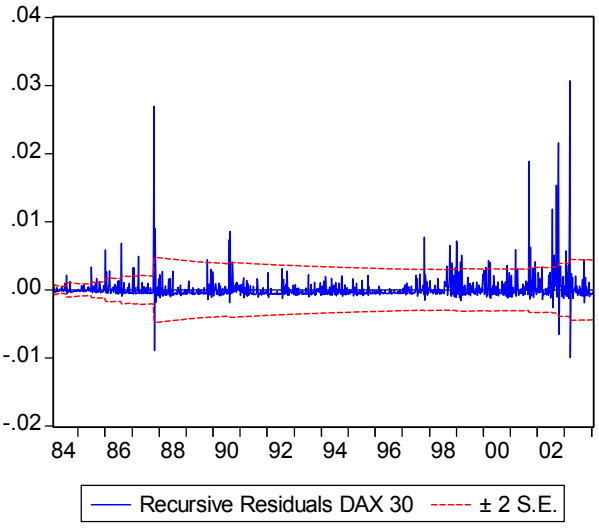
02
One-Step Probability
Recursive Residuals

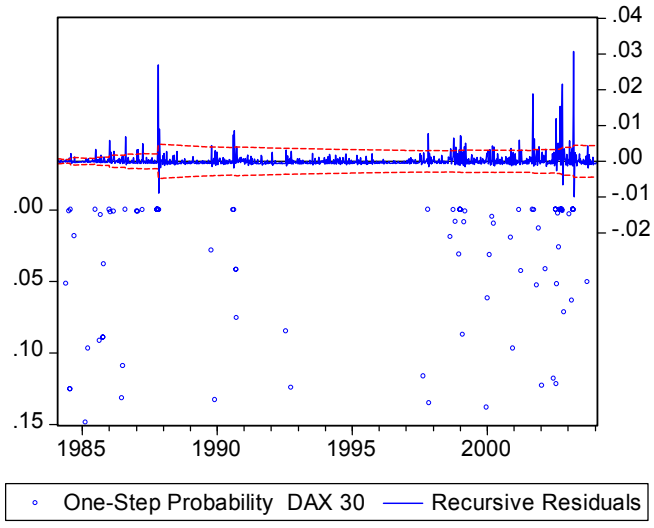
GERMANY

DAX30:









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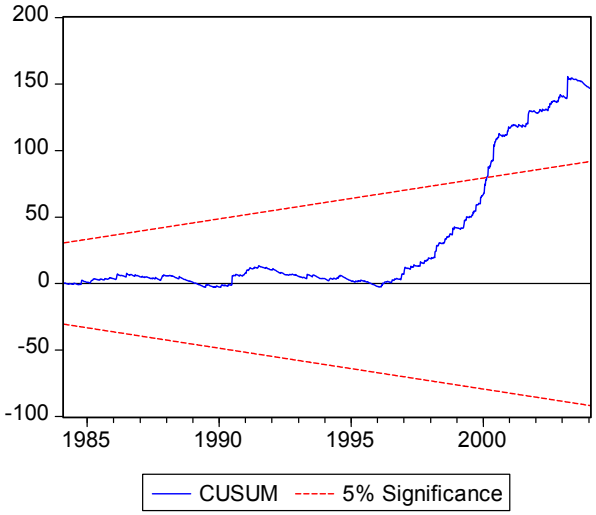
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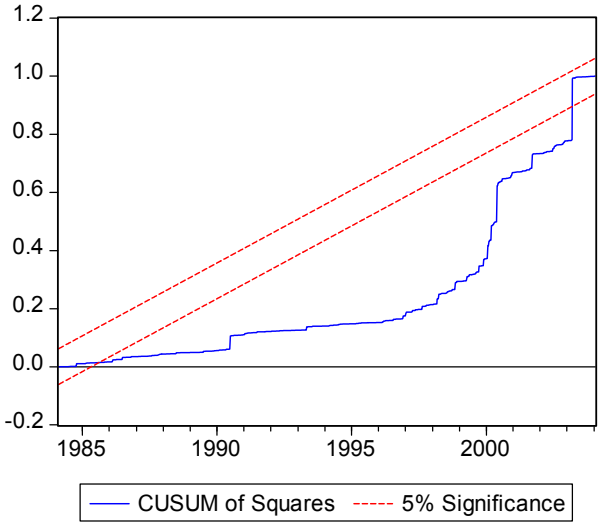
1985
1990
1995
2000
CUSUM
5% Significance


1.2
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0.4
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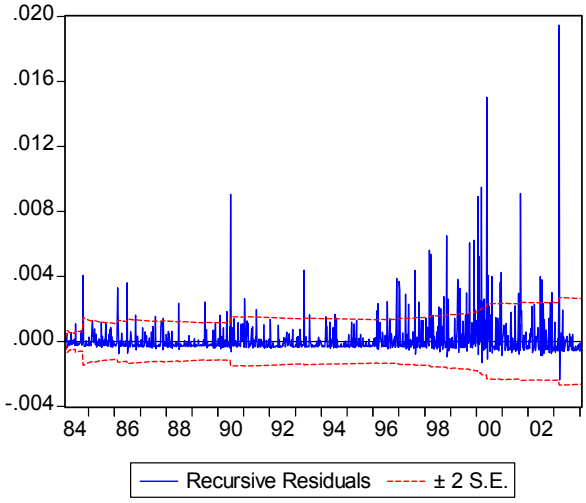
0.0
-0.2
1985
1990
1995
2000
CUSUM of Squares
5% Significance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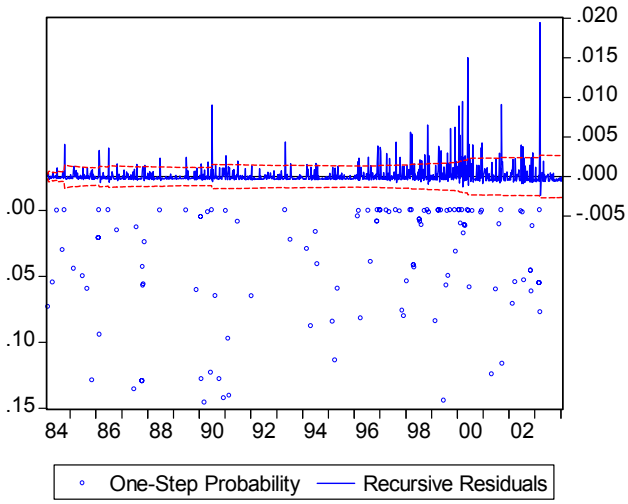
Recursive Residuals
± 2 S.E.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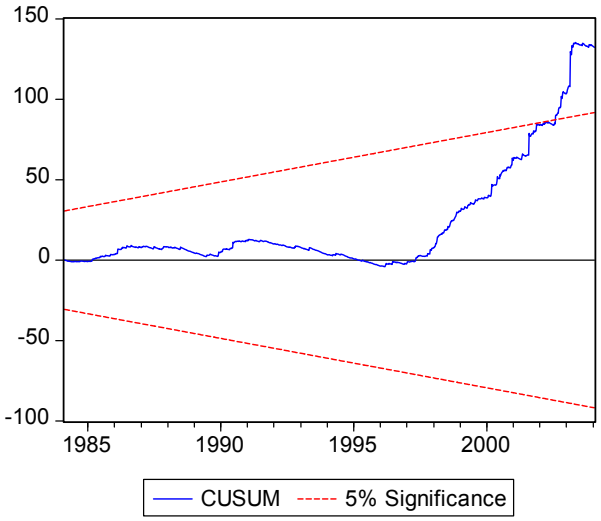
02
One-Step Probability
Recursive Residuals

BAYER: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1985
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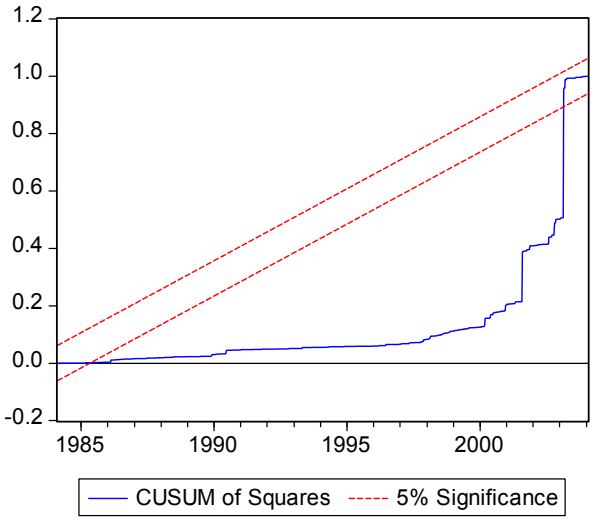
CUSUM
5% Significance


1.2
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1985
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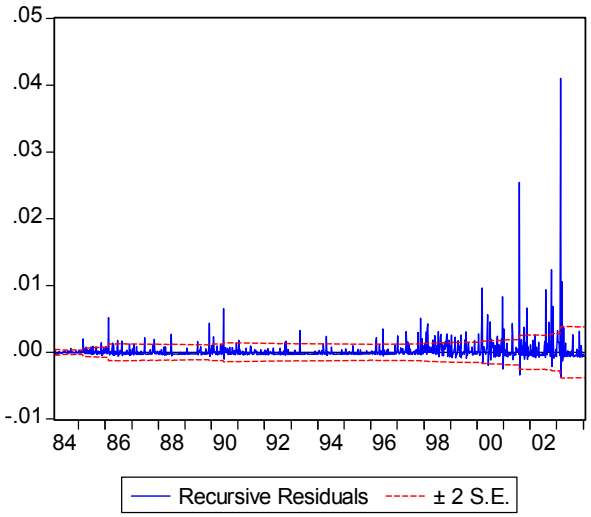
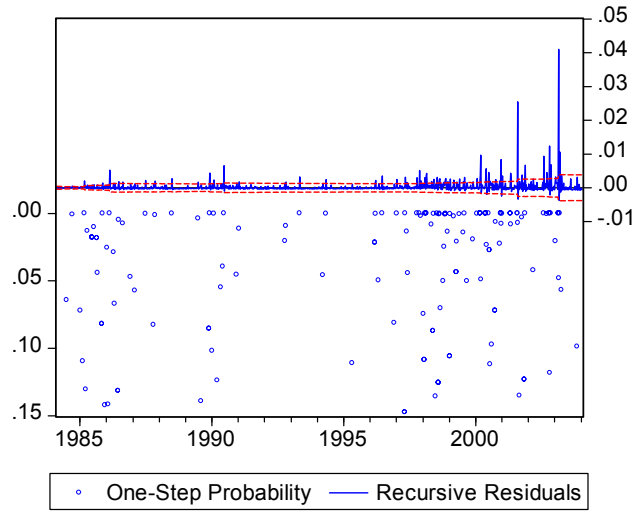
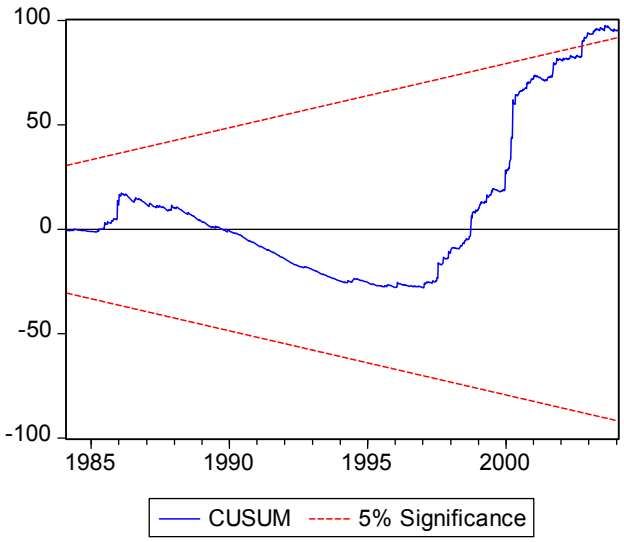
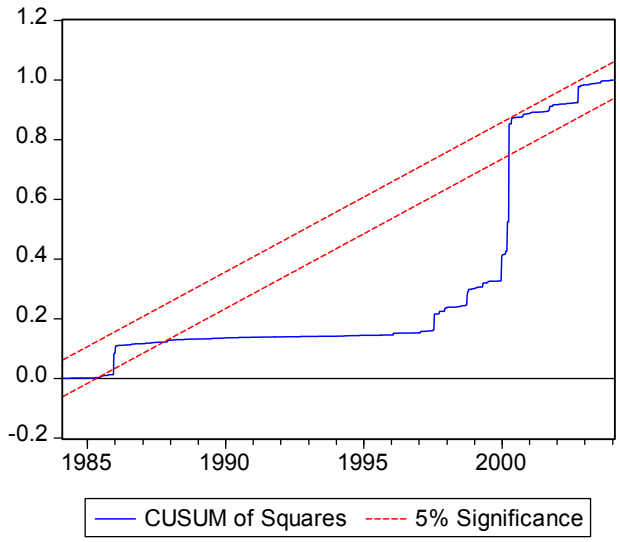
CUSUM of Squares
5% Significance

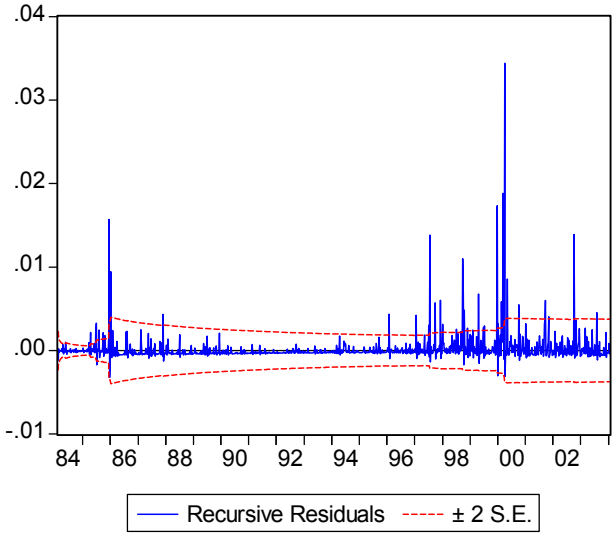


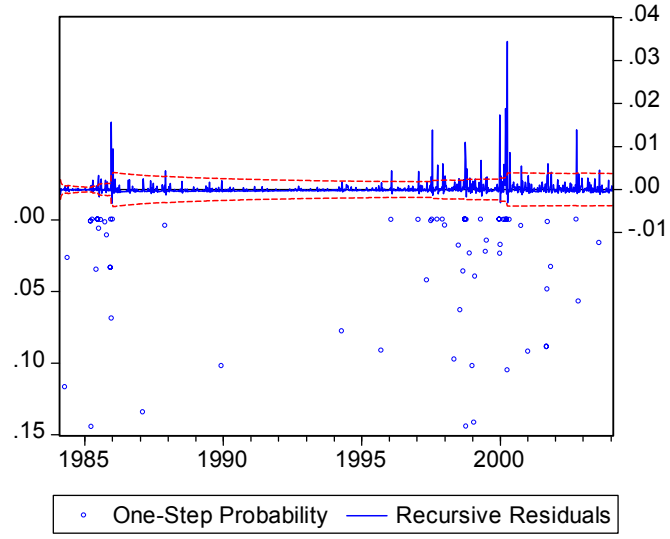


Deutsche Bank:









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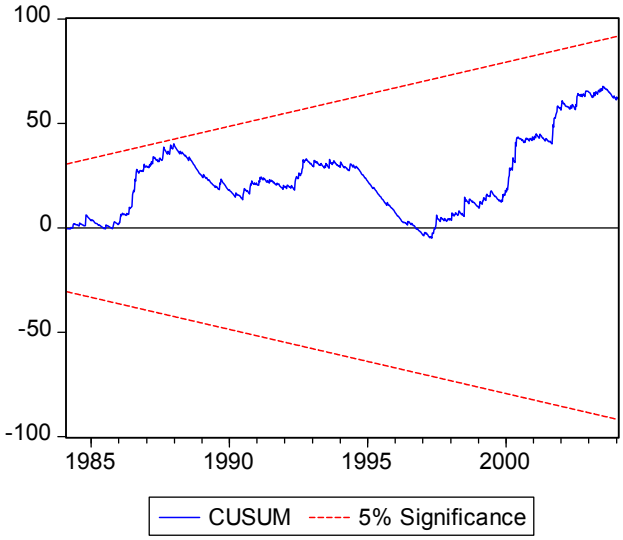

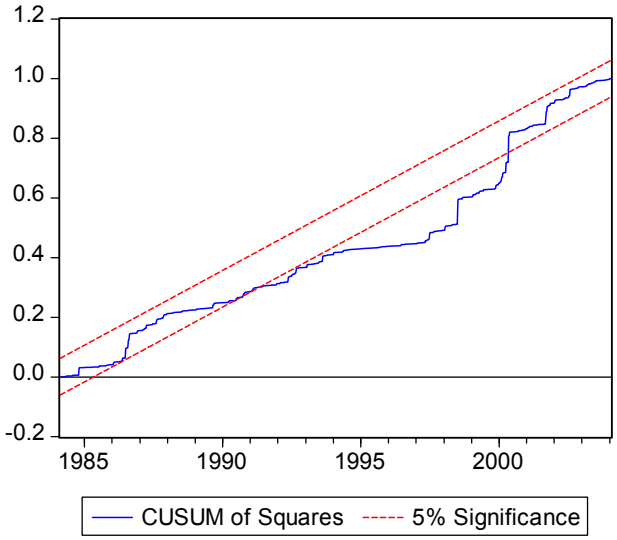

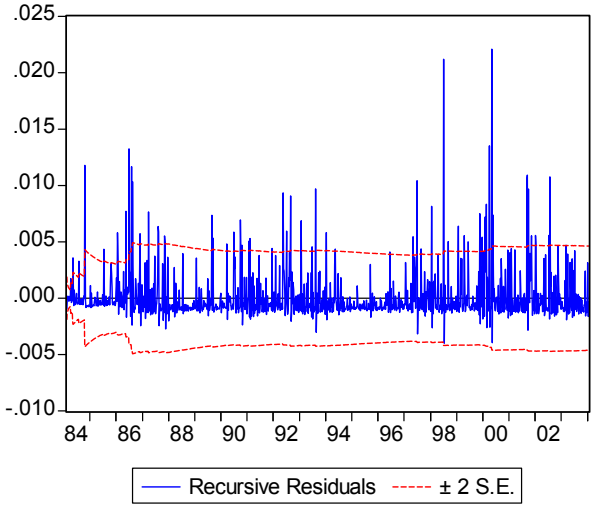

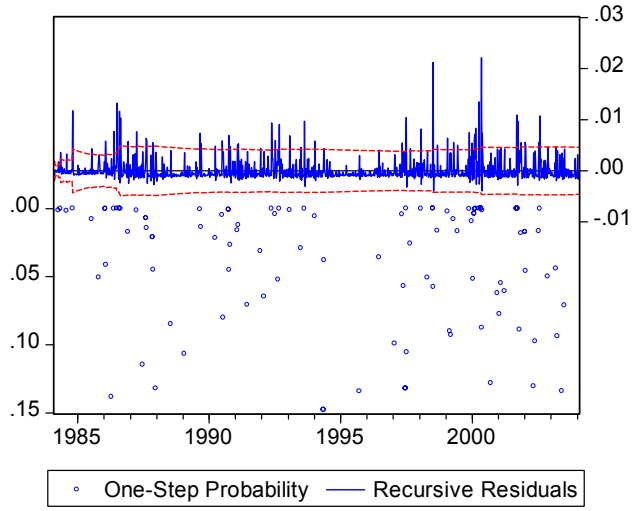

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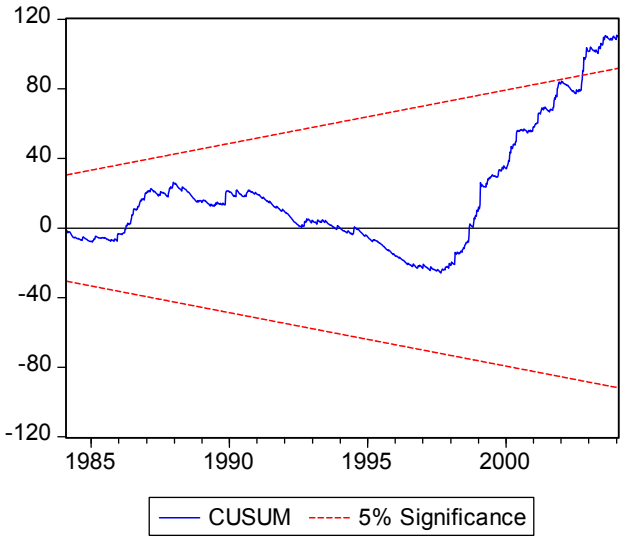

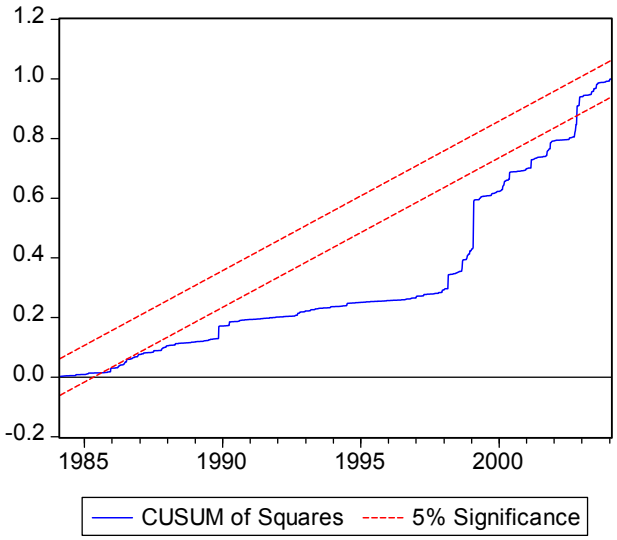

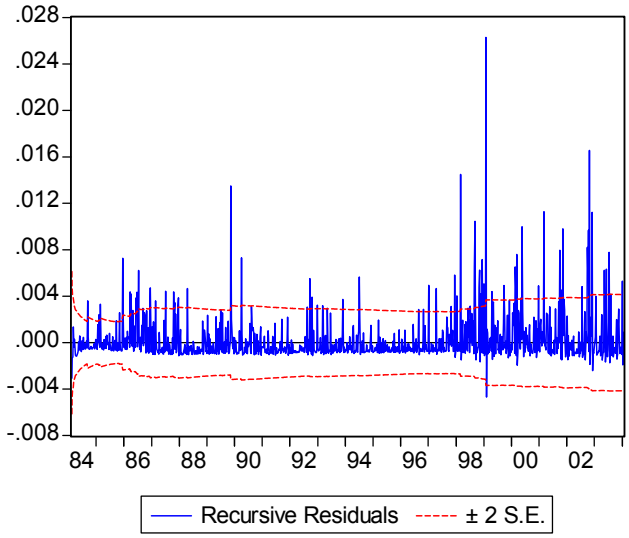
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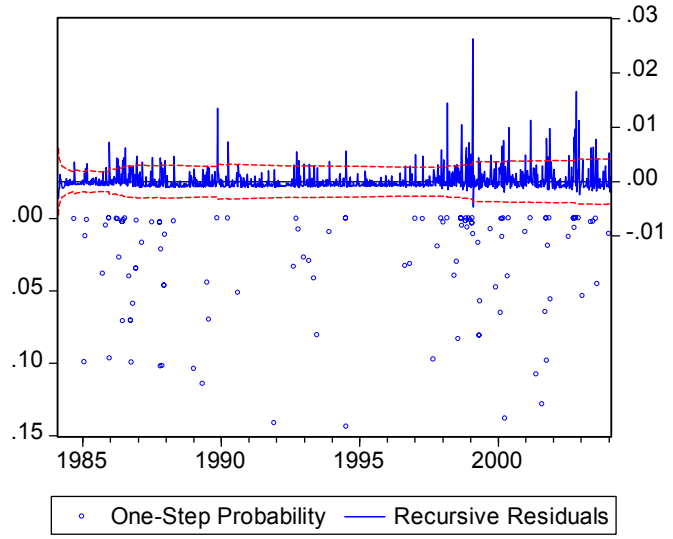
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.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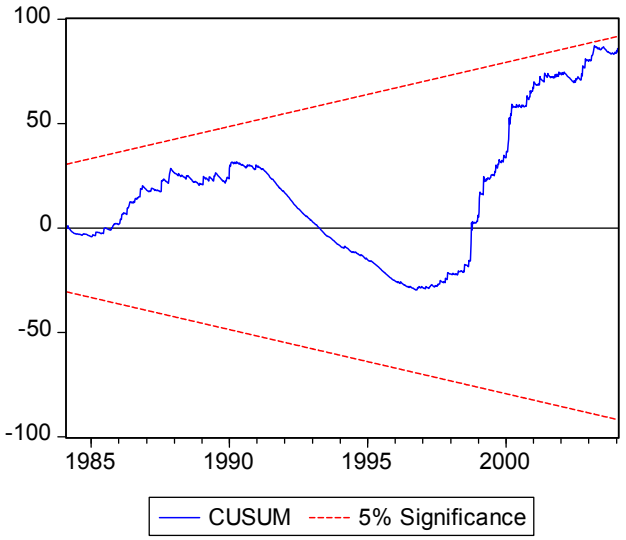
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

RWE:


100
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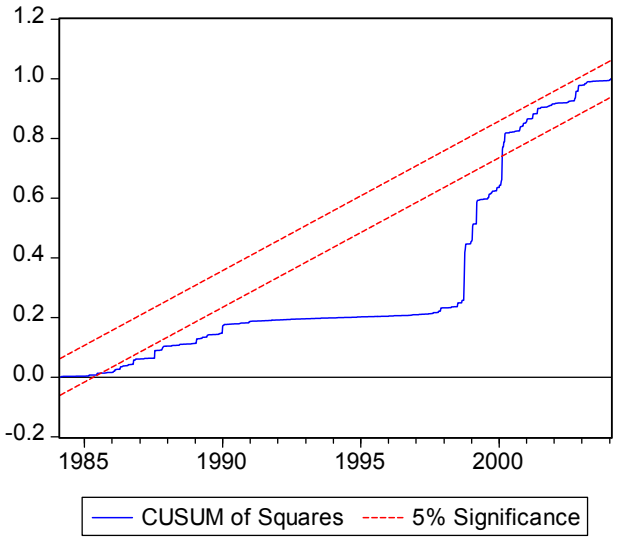
1985 1990 1995 2000
CUSUM
5% Significance


1.2
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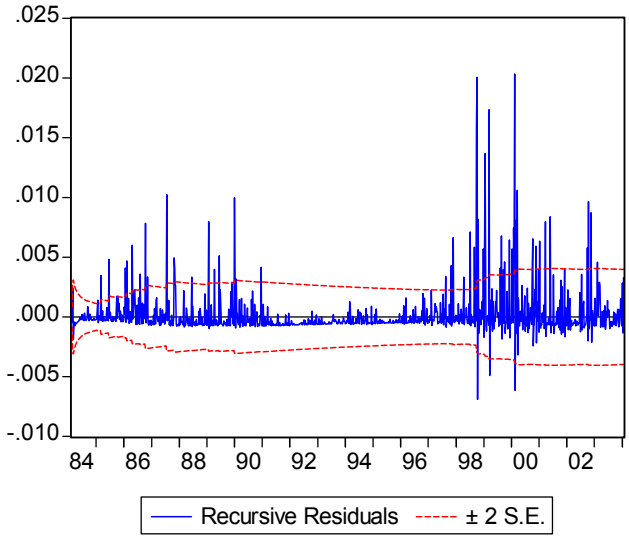
1985 1990 1995 2000
CUSUM of Squares
5% Significance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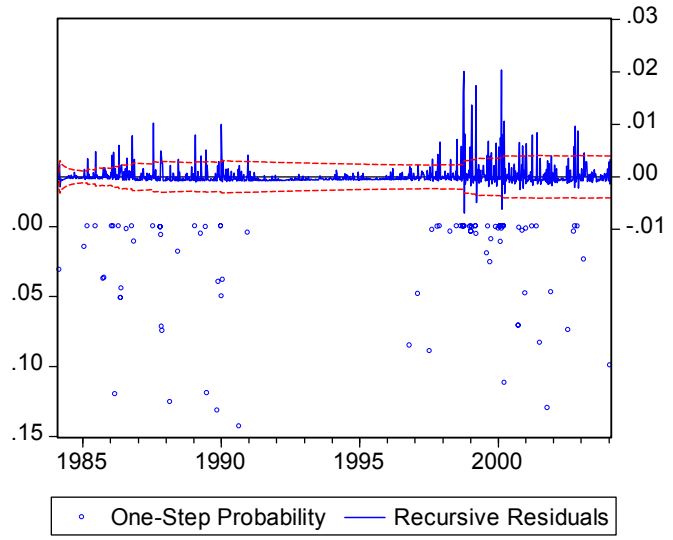
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.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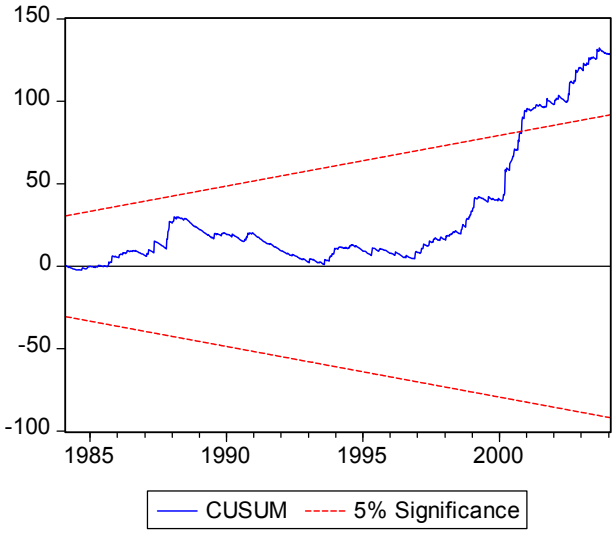
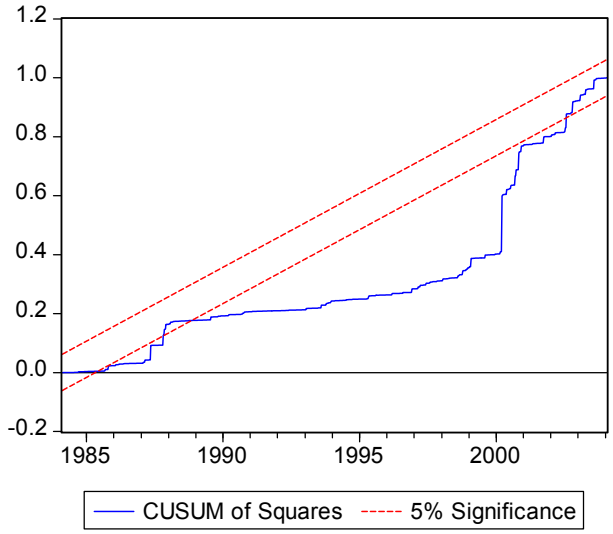
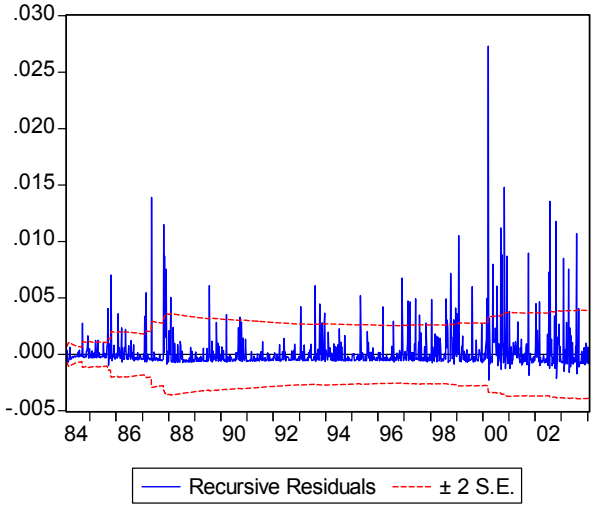
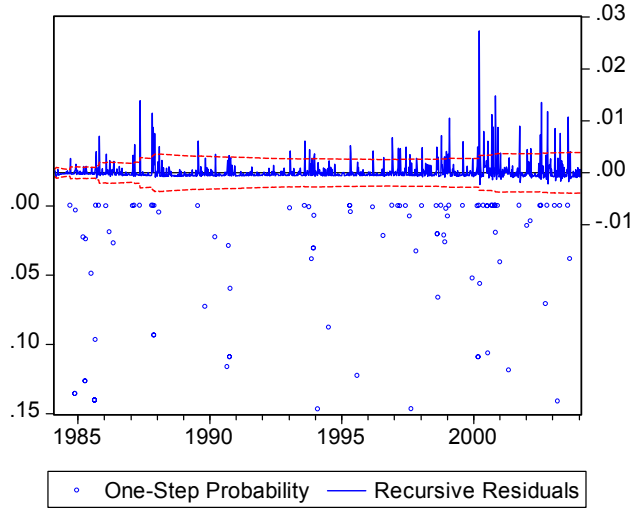
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Schering:









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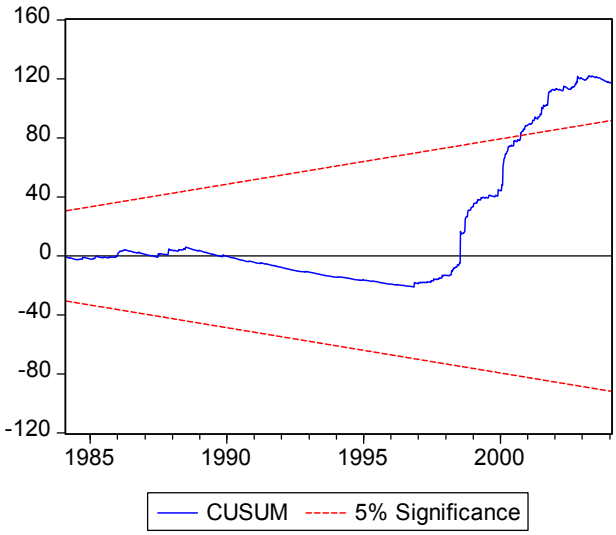
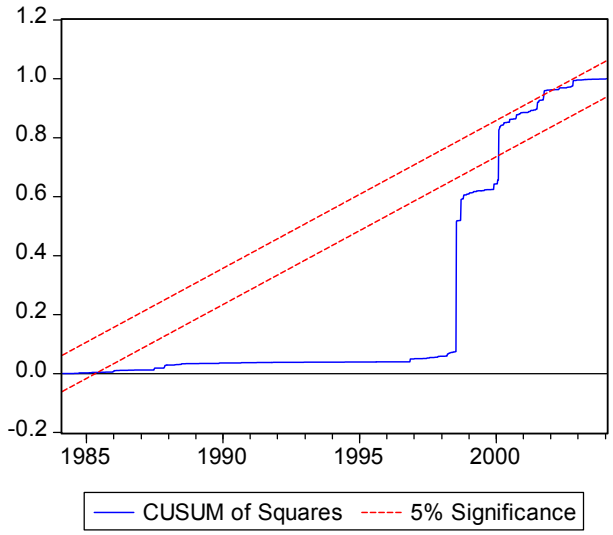
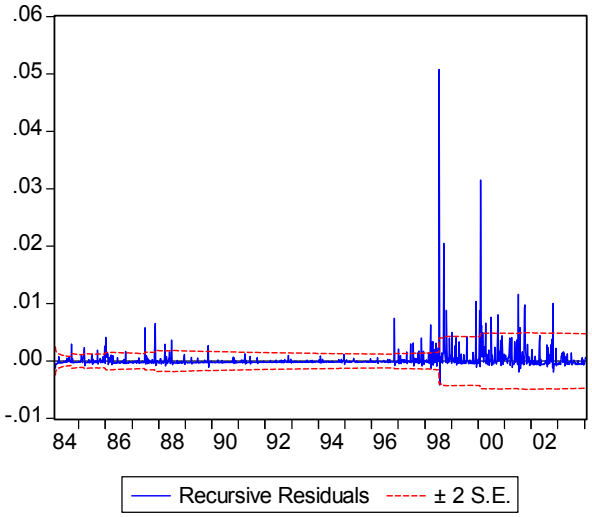
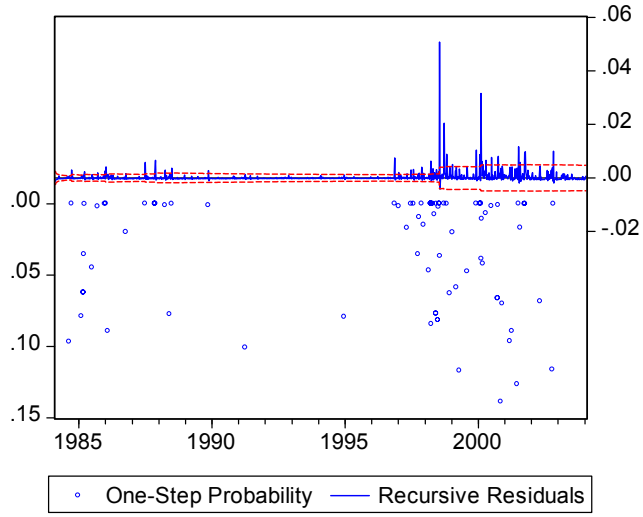
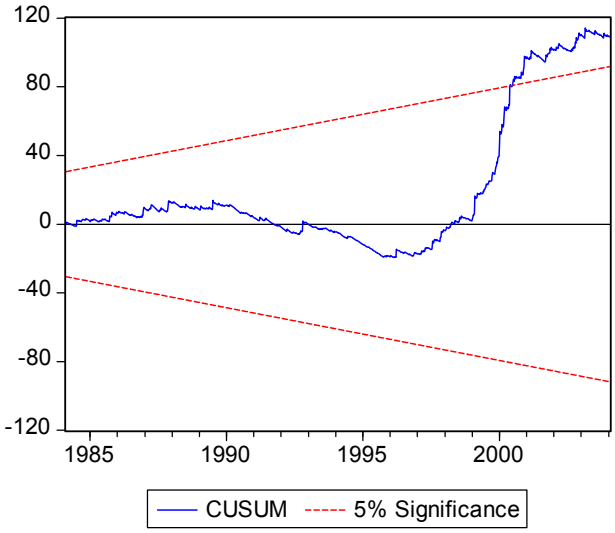


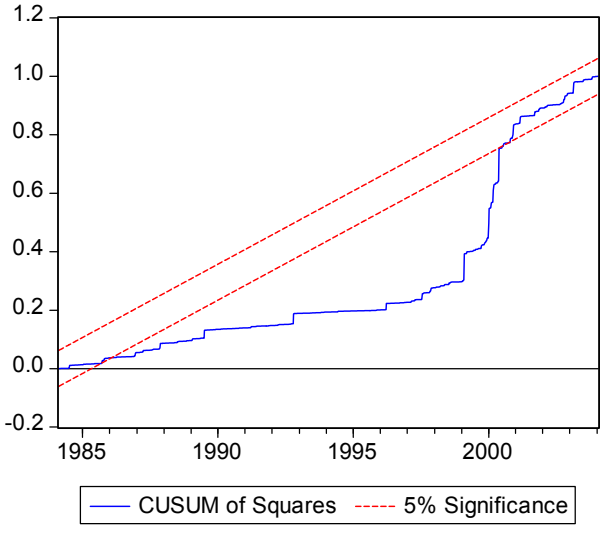


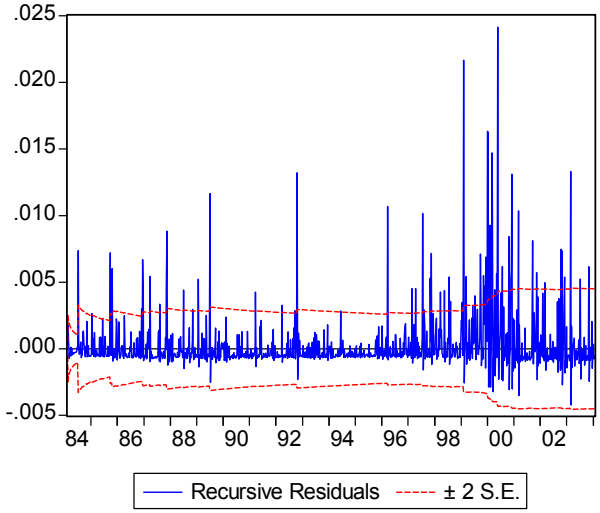


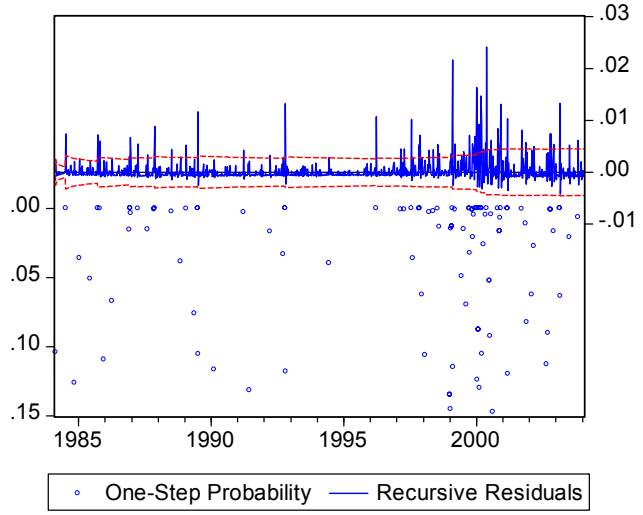


Thyssenkrupp:

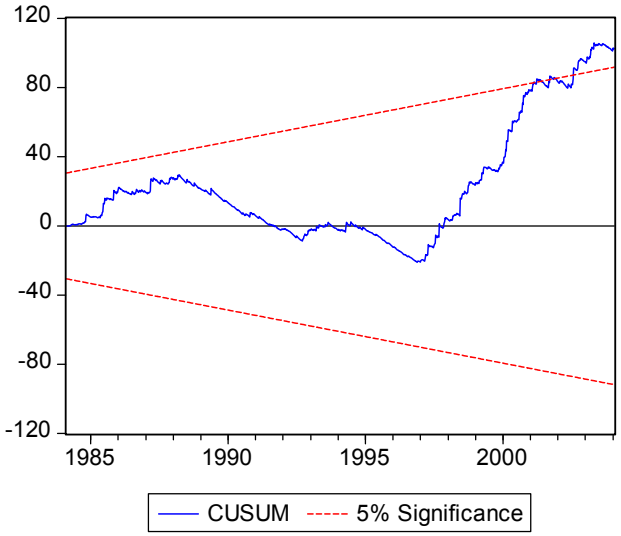








Volkswagen:


120
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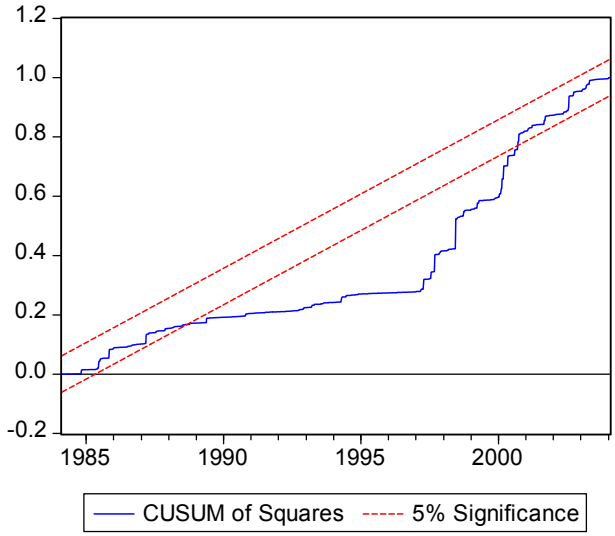
1985
1990
1995
2000
CUSUM
5% Significance


1.2
1.0
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1985
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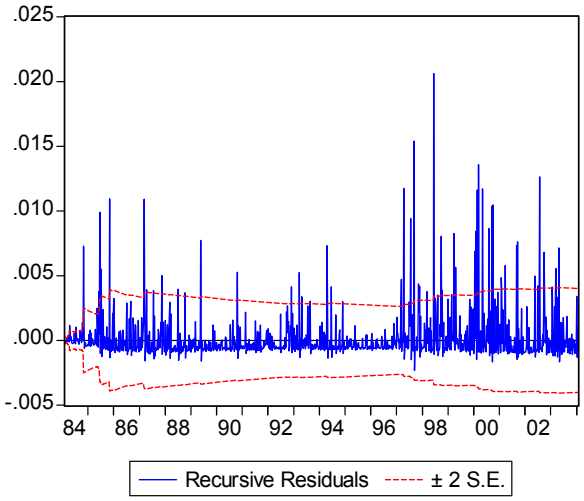
CUSUM of Squares
5% Significance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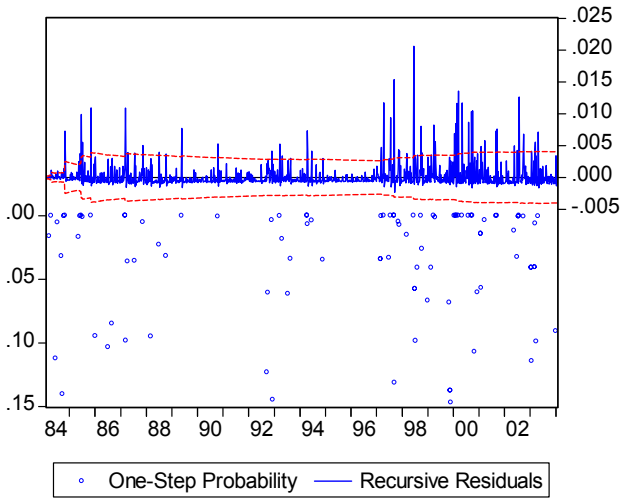
Recursive Residuals
± 2 S.E.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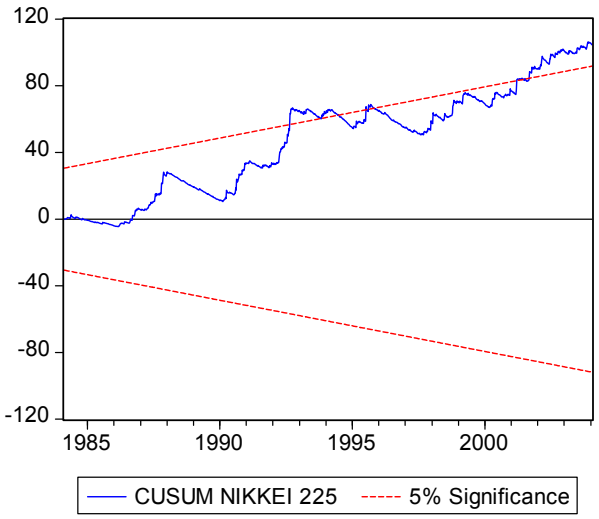
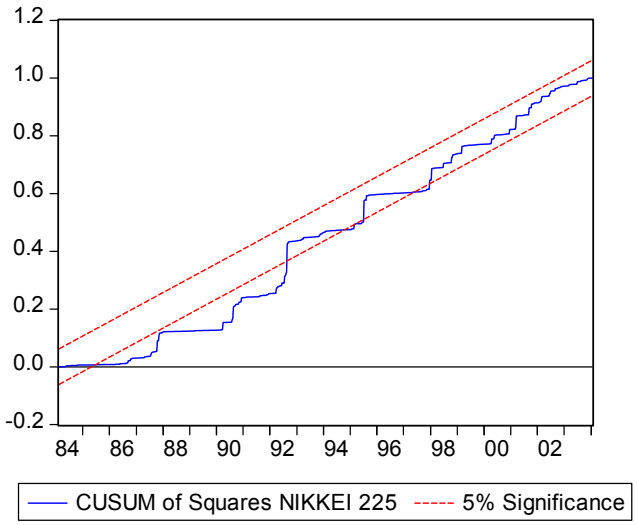
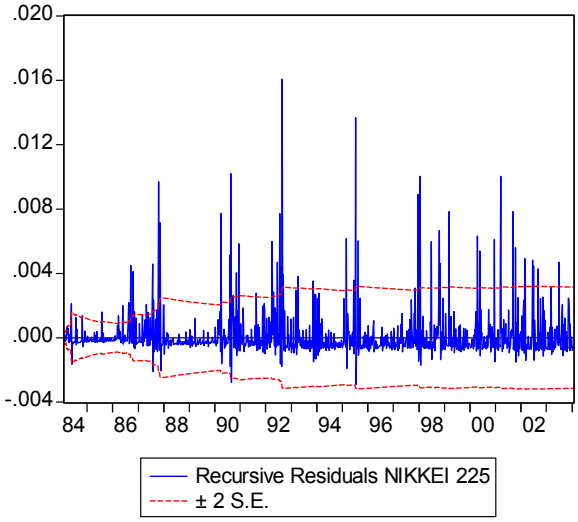
One-Step Probability
Recursive Residuals

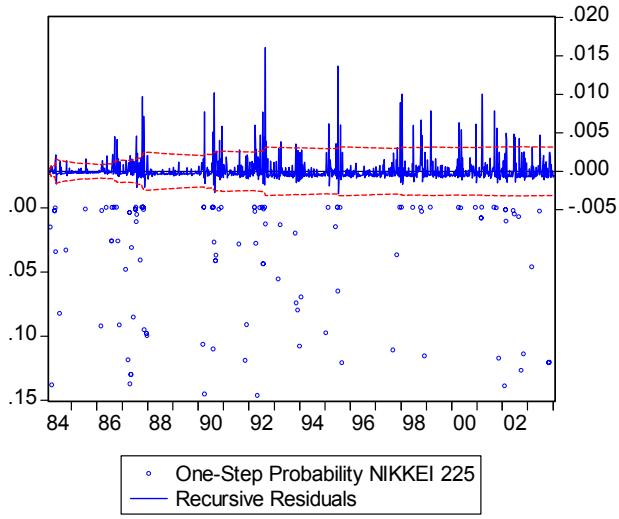
JAPAN

NIKKEI225:









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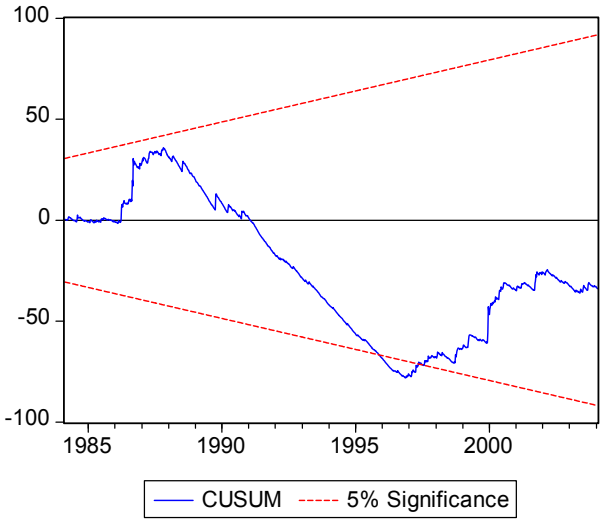
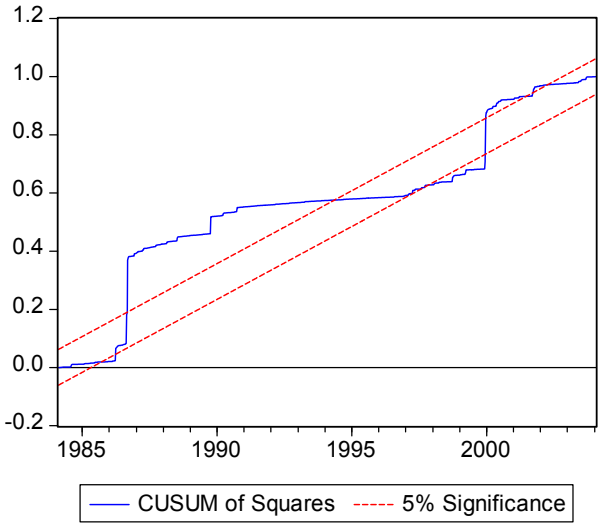
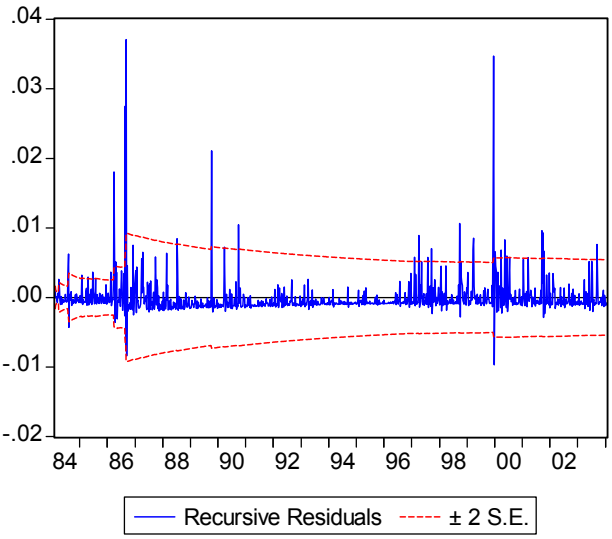
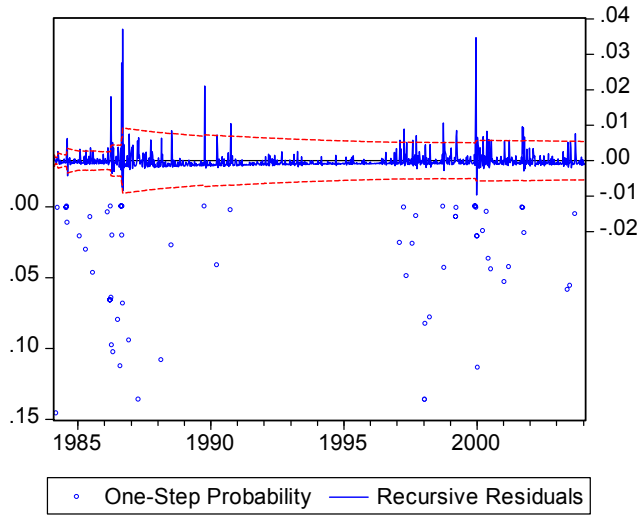
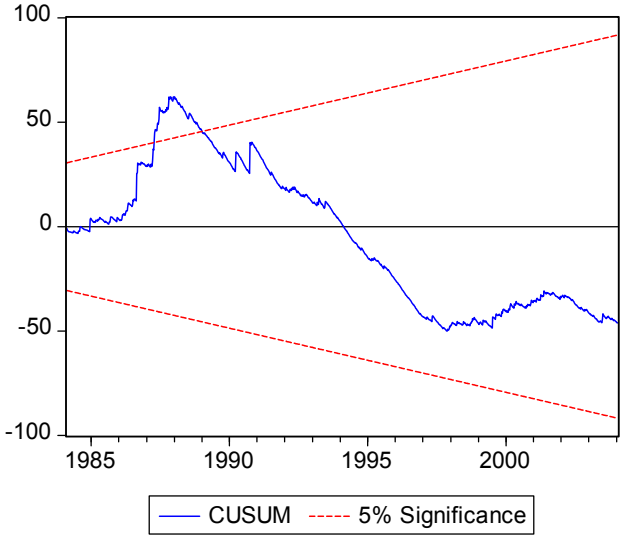


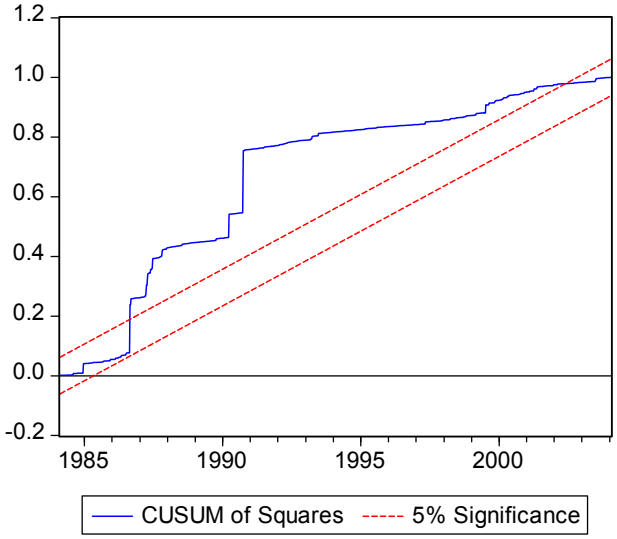


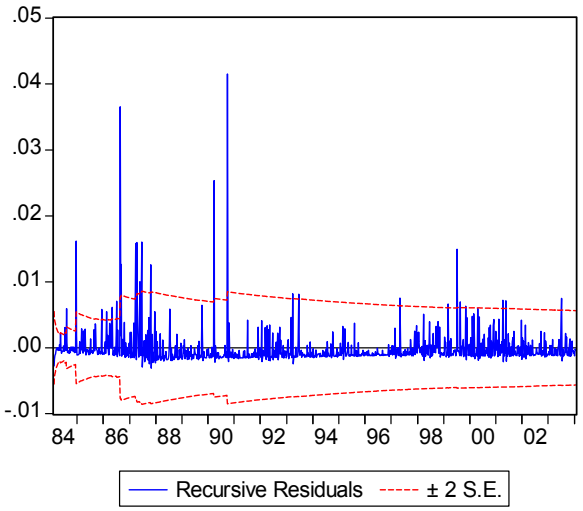




Matsushita Electric INDL:



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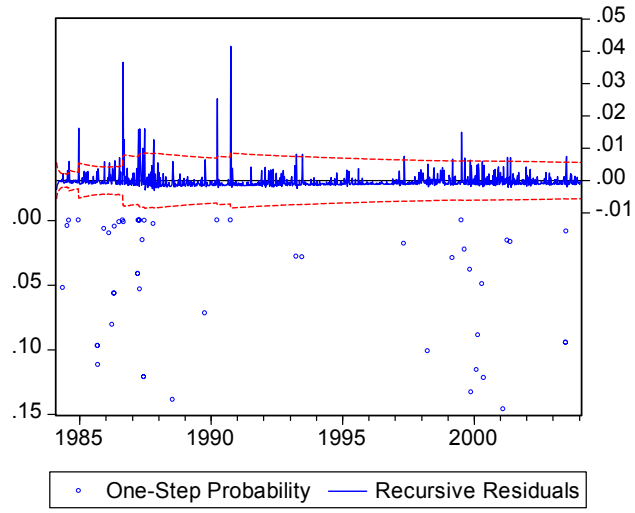
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.


.05
.04
.03
.02
.01
.00
-.01
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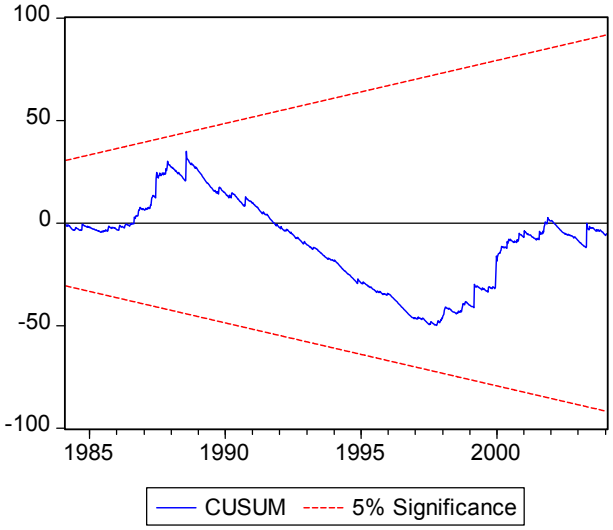
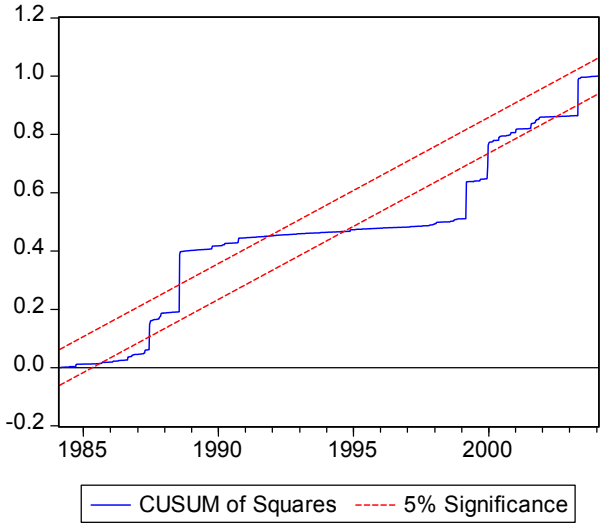
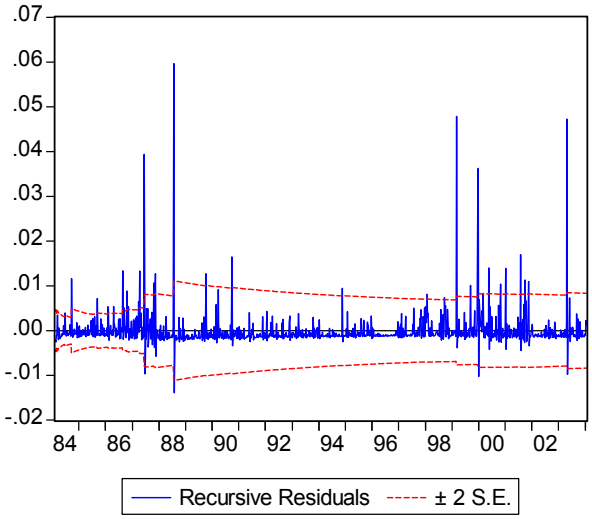
.05
.10
.15
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

SONY:


100
50
0
-50
-100
1985 1990 1995 2000
CUSUM
5% Significance


1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1985 1990 1995 2000
CUSUM of Squares
5% Significance


.07
.06
.05
.04
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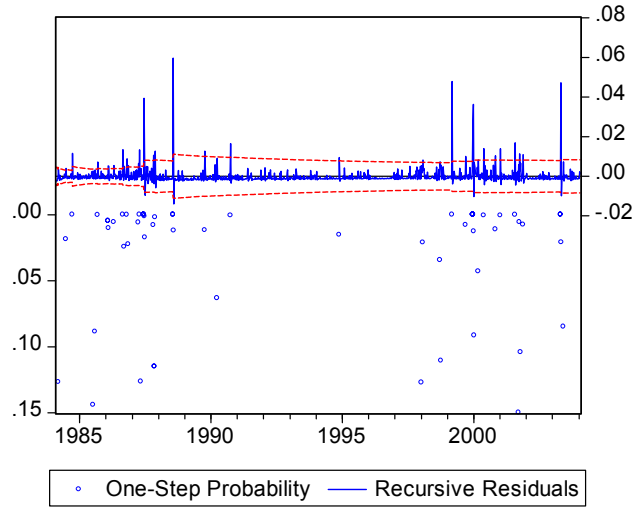
.02
.01
.00
-.01
-.02
84 86 88 90 92 94 96 98 00 02
Recursive Residuals
± 2 S.E.


.08
.06
.04
.02
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-.02
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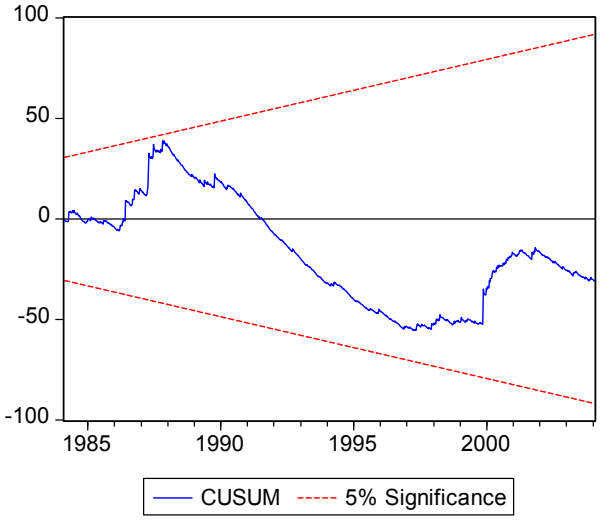
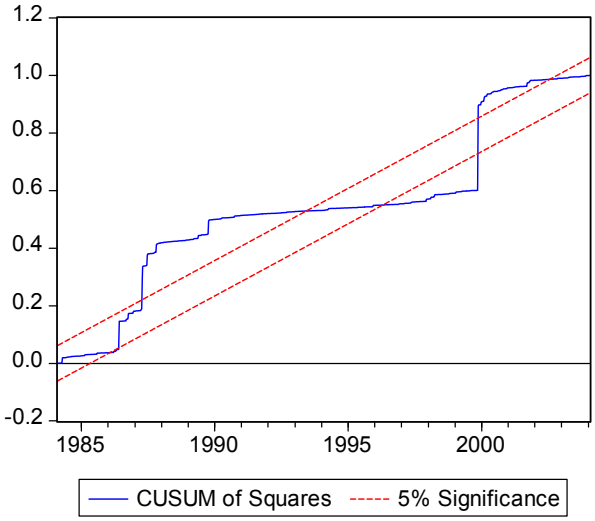
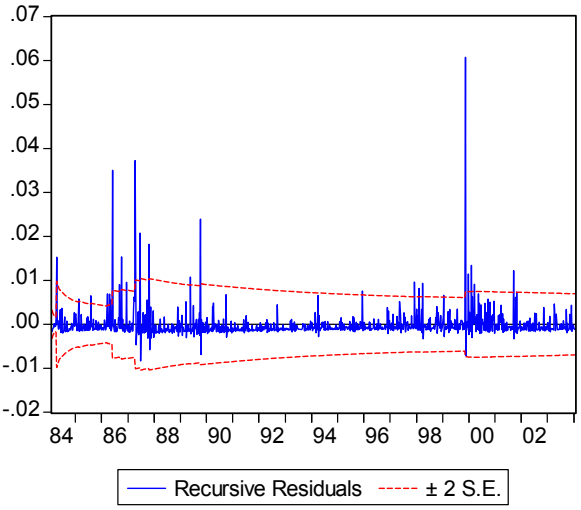
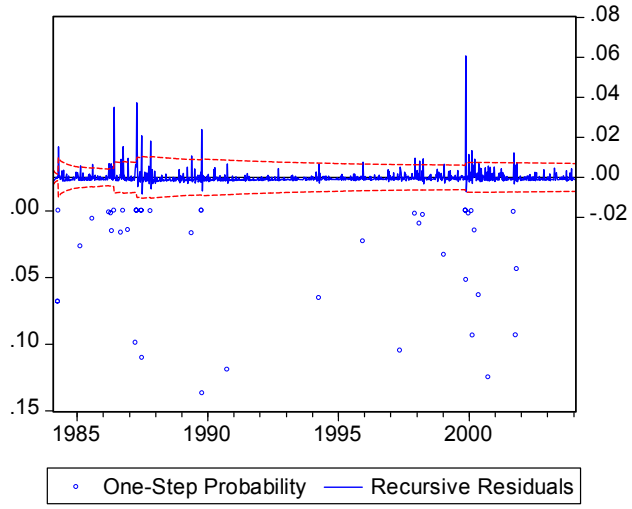
.10
.15
1985 1990 1995 2000
One-Step Probability
Recursive Residuals

Fuji Photo Films:









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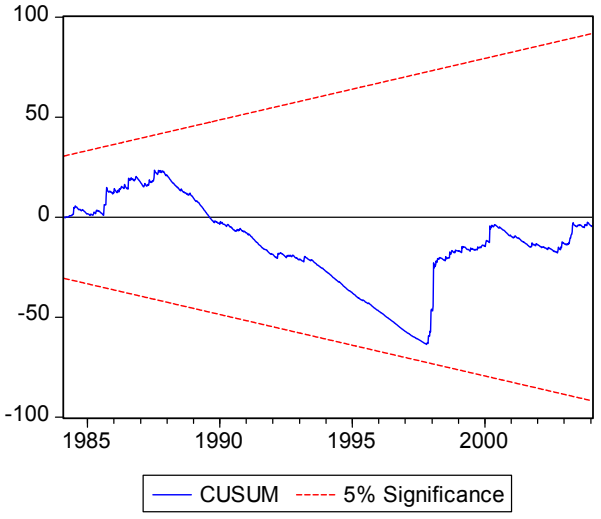
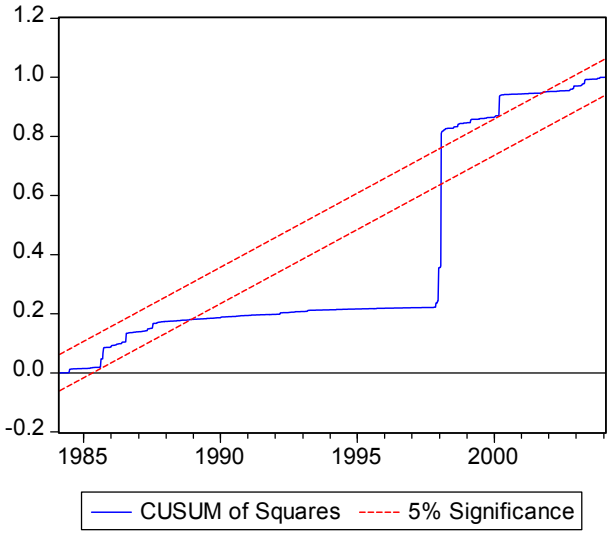
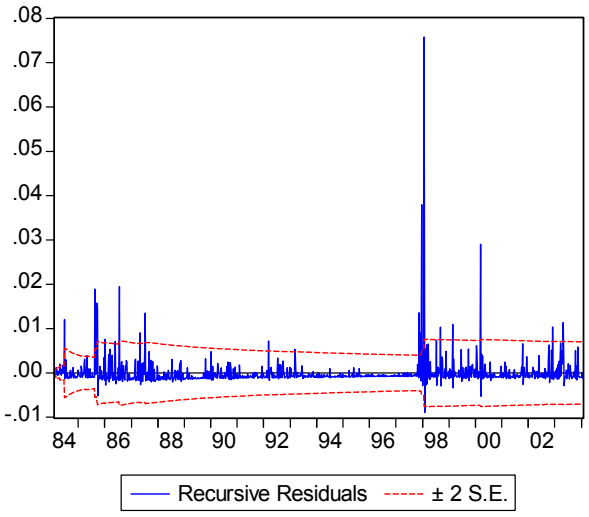
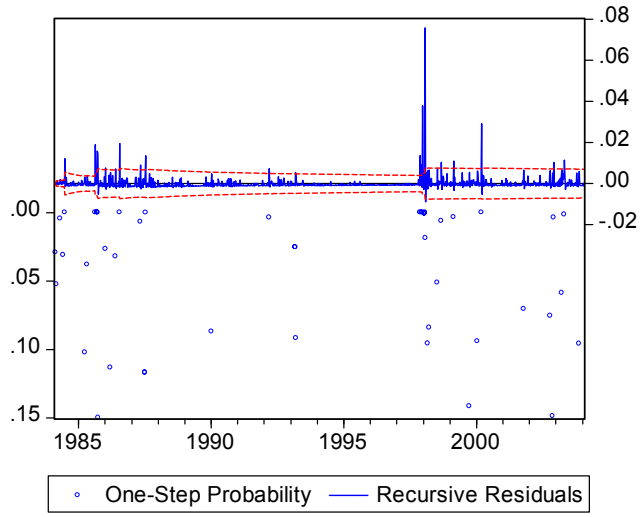
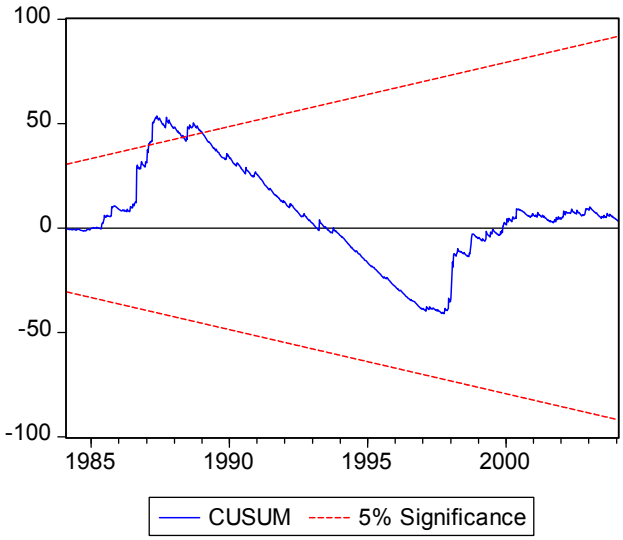


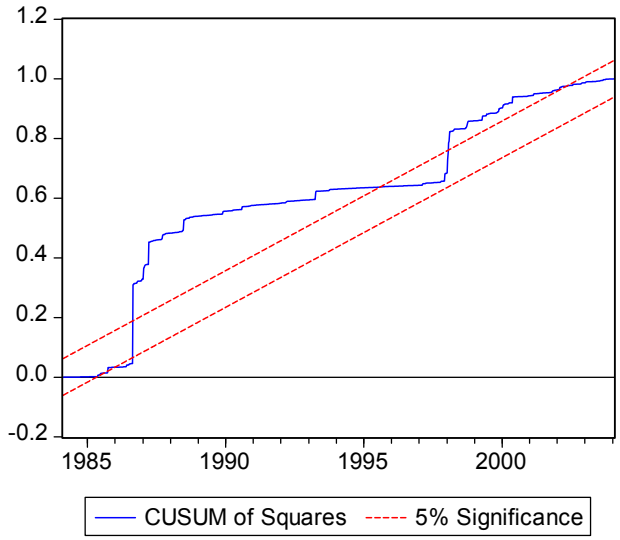


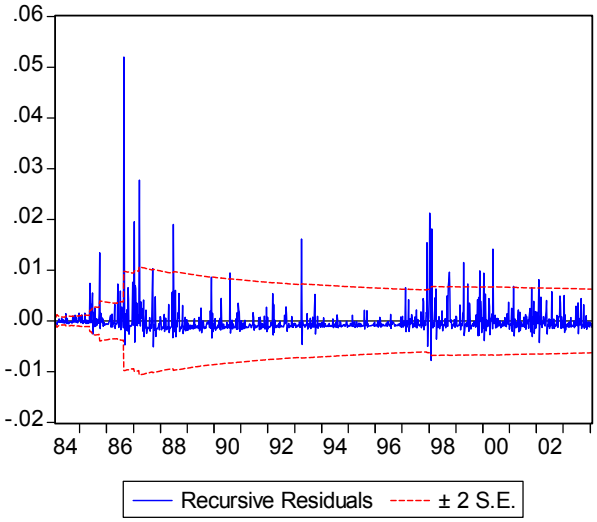


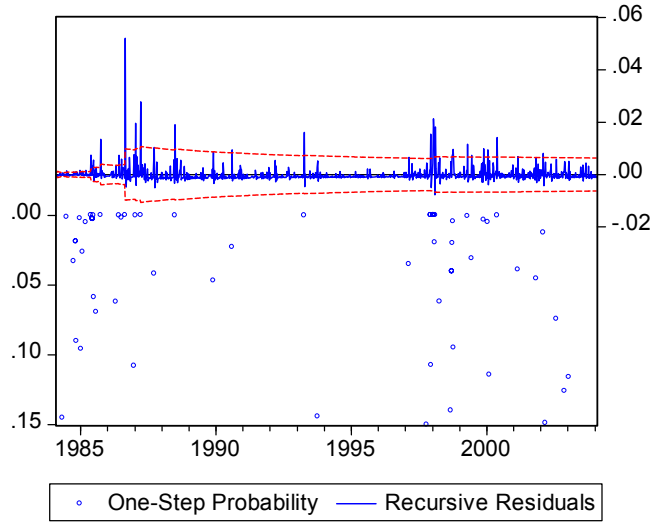


Nippon Steel:









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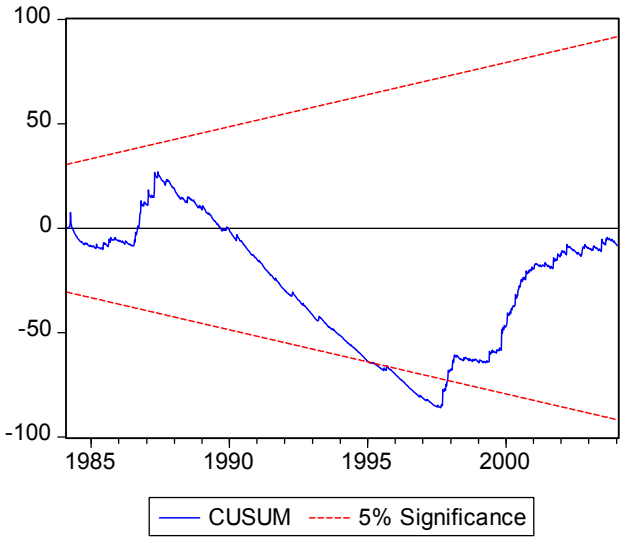

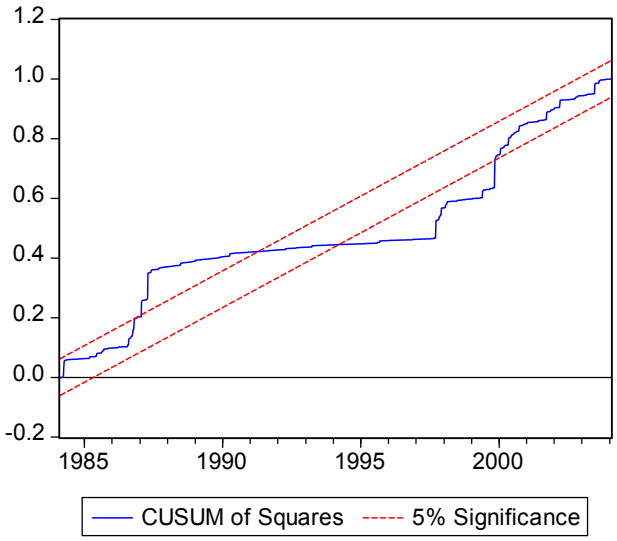

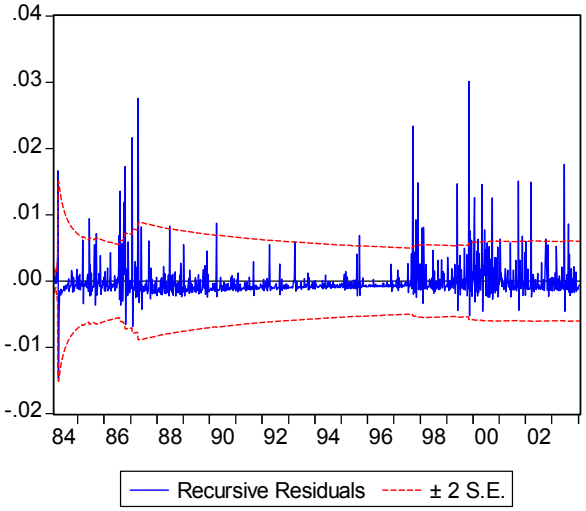

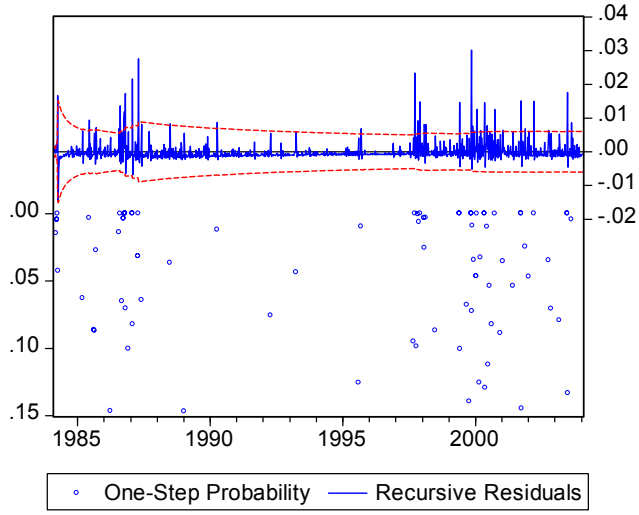

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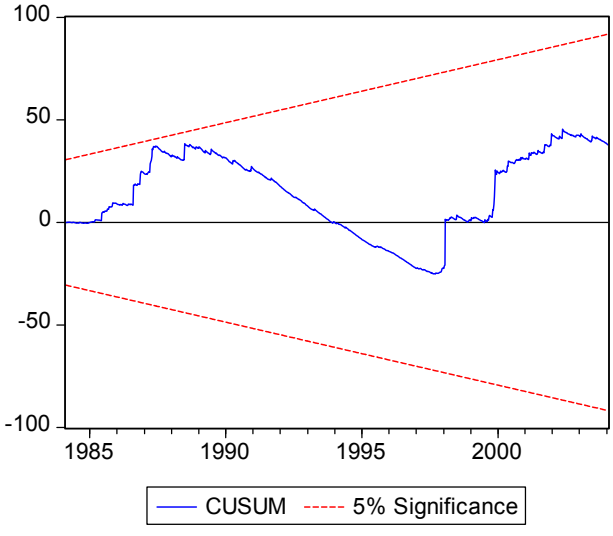
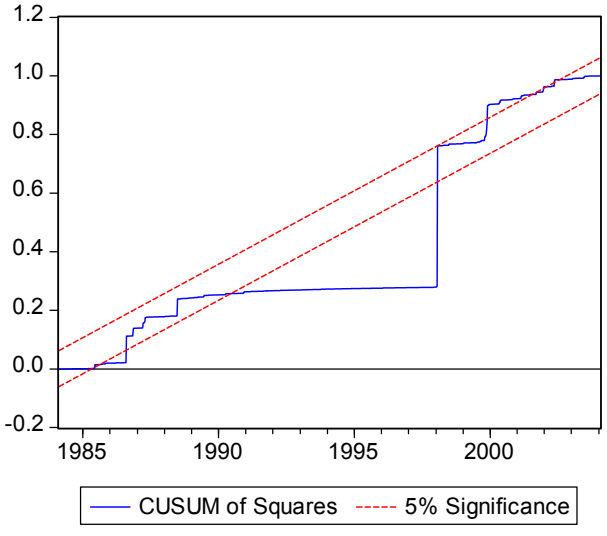
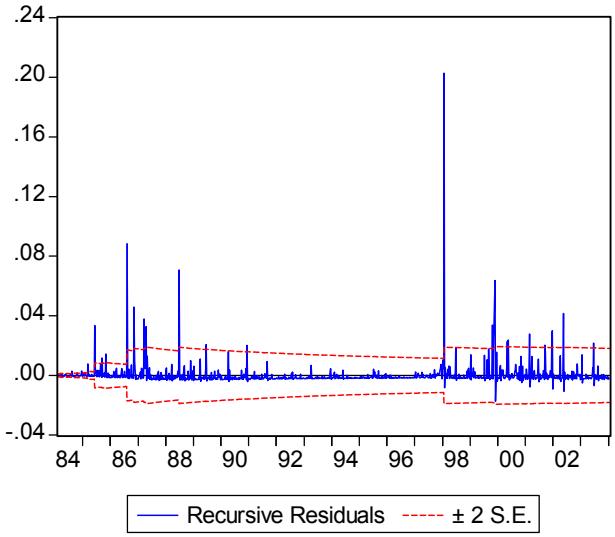
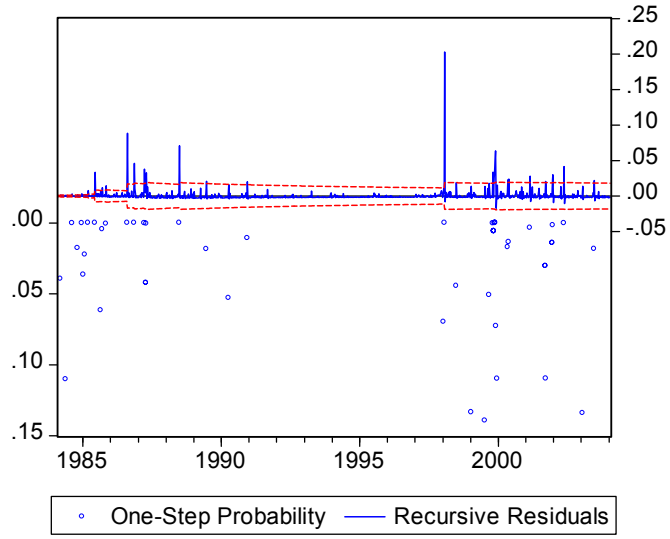
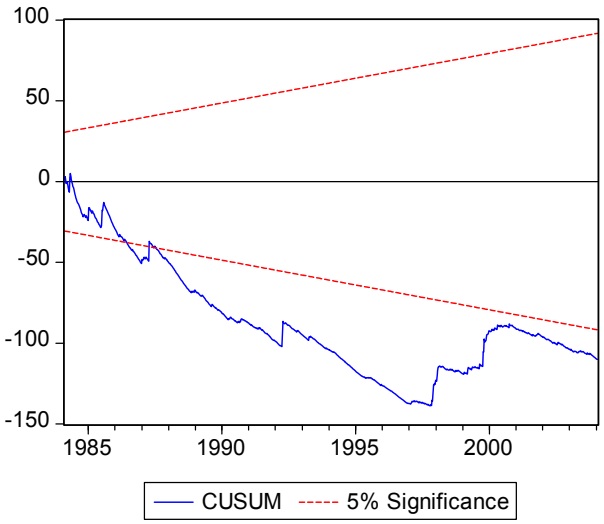


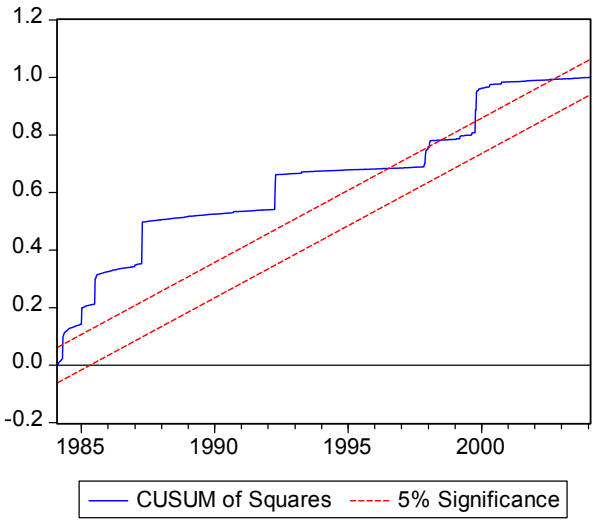


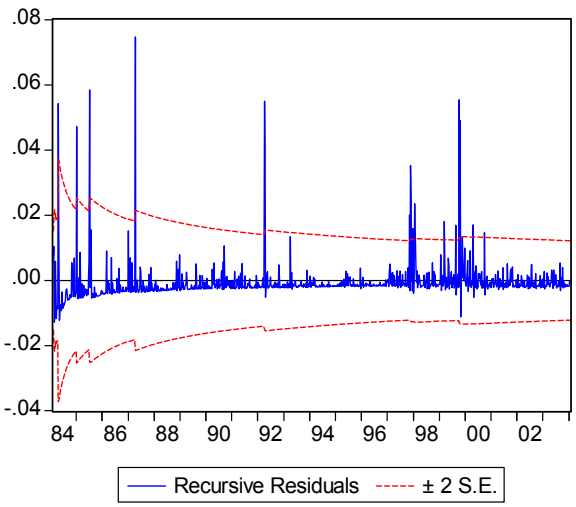


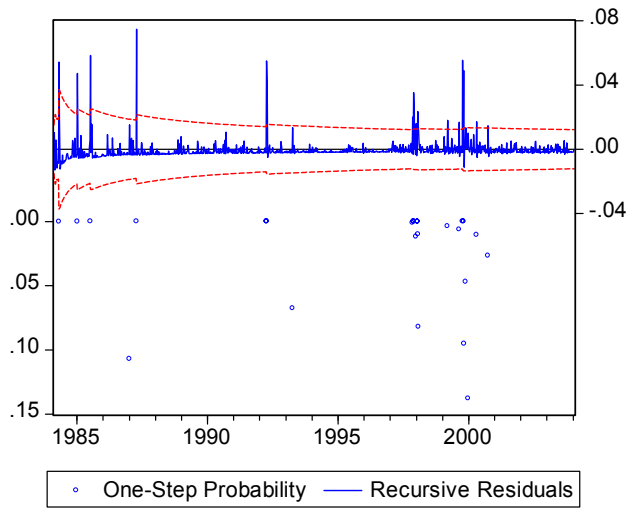


Bank of Yokohama:









***Tokyo Electric Power*:**