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Dissertation Theme

Is inflation rate a stationary process?

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A B S T R A C T

Using conventional unit root tests, like Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) test, we conclude on contradictory results as far as inflation rates and unit roots are concerned. We can see this from various researches that used such tests. In this paper, we will try to focus on the problems which lead to these contradictory results about unit root and inflation and to propose ideal modifications of these tests that have come out in the literature and seem to correct these problems. Our aim is to use such a modification of the tests so as to reach valid results and get the real behavior of inflation rates.

Introduction

It is common for macroeconomic variables to increase or, less frequently, decrease over time. Output increases as technology improves, the population grows and inventions occur; prices and the money stock increase as central banks target a positive rate of inflation, and so on. Many economic theories posit causal relations between economic series that increase over time. Central bank economists have to understand and forecast macroeconomic time series. A serious problem that they face is that those series are often trended or affected by persistent innovations to the process. To try to get round this problem, or at least to understand its possible effects, it is common to test whether series are stationary.

Many contradictory empirical results on the persistence of inflation rates can be found in the literature. Some of the early researches are in favor of non stationarity in inflation rates and others are in favor of stationarity: MacDonald and Murphy (1989), investigating inflation rate for Belgium Canada, the United Kingdom and the United States with quarterly data from 1955 to 1986, found strong evidence for non stationary behavior.

Barsky (1987) found that the U.S. inflation rate evolved from essentially a white noise process in the pre World War I years to a highly persistent, nonstationary ARIMA process in the post 1960 period. He believes that this change is connected with the appearance of ex post Fisher effect for the first time after 1960[1].

[11] He refers to *ex post Fisher effect* as a strong correlation between nominal interest rates and realized inllation

The essence of this change is that interest rates displayed a zero (or slightly negative) correlation with contemporaneous inflation prior to 1930, while a strongly positive correlation has been observed since about 1960.

Wickens and Tzavalis (1992) investigated monthly U.S. data. They used a class of unit root tests suitable for break point selection (Zivot and Andrews 1992). They clearly reject the unit root hypothesis in which the process is assumed to be structurally stable with a one time shift in its mean at an unknown date, in favour of the alternative hypothesis of a stationary process with a shift in the mean. The main finding, however in this paper, is that the real interest rate seems to contain far more information about future inflation than the slope of the yield curve. In general they showed that the forecasting ability of the term spread about future inflation is very poor.

Kenneth M. Emery (1994), in the same way, concludes that inflation rates are not stationary. This study finds that the time-series properties of inflation have changed since the end of 1981. Specifically, the inflation rate has become less persistent and, in fact, can best be characterized as white noise during the 1980s. This description of inflation contrasts sharply with the highly persistent characteristics of inflation during most of the post-Accord period. Instead, recent movements in inflation closely resemble the behavior of inflation during the U.S. gold standard.

Culver and Papell (1997), use both Augmented Dickey Fuller and KPSS tests, and appears to be a unit root in inflation for most of the thirteen OECD countries using post-war data. They investigate this further by estimating sequential break models, which allow for breaks in the intercept of the trend function, and panel data models, which incorporate cross-section variation. The sequential trend break results do not provide much evidence against unit roots in infation. With breaks, they cannot, however, ever reject the unit root null for seven of the countries. The panel data results provide much more evidence against a unit root in infation rates. They incorporate cross-section variation and find strong evidence against the unit root hypothesis for not only the thirteen countries as a whole but for a number of other selected panels. Results with smaller panels indicate that, for the inflation rate, the non-rejection of the unit root hypothesis is fragile to cross-section variation.
They support their thesis by saying that these panel data results are particularly compelling given that the panel model can provide significant improvements in statistical power when compared to unit root tests for individual time series.

However, Buster and Westerland (2006) argued that the panel unit root test employed by Culver and Papell (1997) is based on unrealistic assumptions and that there is a need to reevaluate the results while allowing for more general data generating processes. Results obtained from a large battery of recent panel data unit root tests suggest that the stationarity of inflation holds even after allowing for general forms of cross-sectional dependence and multiple structural breaks in each cross-section.

On the other hand, Rose (1988) clearly found for 18 countries that quarterly inflation rates were stationary during the sixties, seventies, and eighties. And this was his findings with monthly U.S. rates from 1948 to1986 too.

One thing most of the previous works have in common is the methodological approach of applying augmented Dickey –Fuller tests. Because of the contradictory results, researchers started to apply different unit-root tests. In 1995, Hassler and Wolters employed various tests to investigate stationarity behavior of inflation rates. They used a more descriptive method by Tiao and Tsay (1983), traditional unit root tests such as the Dickey –Fuller and the Phillips Perron tests, and KPSS test that has the stationarity assumption as null hypothesis. They examined monthly inflation rates of five industrial countries. The application of tests against stationarity as well as tests against a unit root yielded again contradictory results. They use Geweke Porter-Hudak (GPH) estimator. GPH estimator is theoretically valid for $0<d<0.5$. Thus, if the estimate of the memory parameter is on the verge of stationarity, we need to consider an estimator which is consistent for $d>0.5$ as well as $0<d<0.5$. Indeed, the estimates of the inflation rates for five industrial countries in Hassler and Wolters lie around 0.5.

Thus, it is an important issue to correctly estimate the degree of persistence. In the recent studies, much of the empirical evidence supports that inflation series is fractionally integrated with a differencing parameter that is significantly different from zero and unity. In other words instead of dealing with I(0) process or I(1) process, we turn to I(d) which has a better description of inflation rates. We conclude, then, to use Autoregressive Fractionally Integrated Moving Average (ARFIMA) models when seeking to describe the behaviour of inflation rates. Their main advantage is that they allow us to analyze the long run behaviour of the series with their own memory parameter. Evidence in the literature for long memory in major countriesí CPI-based inflation rates is shown to generalize to both CPI- and WPI-based inflation rates for other industrial as well as developing countries. This evidence implies that policymakers may use fractionally integrated models of inflation to good advantage in modeling and forecasting the path of inflation rates.

On this aspect, Jin Lee (2005)[2] finds it important to estimate the degree of persistence, for example, when we analyze the impulse response of unanticipated shock to the inflation rate. He uses a way of estimation as well as of hypothesis testing, which is valid for both stationary and non-stationary long memory processes. Using wavelet-based regression estimator and exact local Whittle estimator to estimate the memory parameter in the monthly US inflation rate (from 1971:1-2003:4), found that the estimates of ***d***

[2] ´´Estimating memory parameter in the US inflation rate´´

range from 0,78 to 1,04. This means that the inflation rate follows non-stationary process, which is not statistically different from I(1).

In the same way, Baum, Barkoulas, Caglayan[3], test for fractional dynamics in CPI-based inflation rates for twenty-seven countries and WPI-based inflation rates for twenty-two countries. The fractional differencing parameter is estimated using semiparametric and approximate maximum likelihood methods. They provide evidence that long memory in the CPI-based inflation rate, as well as in the WPI -based inflation rate, is a general phenomenon for industrial countries as well as for a number of developing countries. To that end, they demonstrate that an ARFIMA model is an appropriate representation of the stochastic behavior of international inflation rates and that long memory is a common feature for the countries studied.

Gadea Sabaté and Serrano (2003) moved a step forward. What is recently being debated is that the long memory phenomenon may just be a consequence of structural changes. They locate the problem of contradictory results in neglecting the potential presence of structural changes in inflation when estimating its long memory parameters. To that end, their empirical exercise is carried out for the inflation series of the UK, Italy and Spain during the period of 1874–1998. They used a wide range of unit

[3] ´´Persistence in international inflation rates´´

root tests (DF, PP, NP, KPSS) and selected to use Geweke and Porter_Hudak (GPH) estimator to get the degree of persistence (*I(d)*). They found that the fractional integration parameters corresponding to the period 1874–1998 point to long memory, with ***d*** values of around 0.4 for the UK and Italy and 0.5 for Spain. However, when including the structural breaks that have been endogenously detected for each series (using the method of Bai and Perron for multiple structural brakes), basically the impact of the World Wars (the Civil War in case of Spain) and the oil shock of the 1970s, the memory are significantly reduced. In this way, the greater the intensity and number of breaks detected in a series, the bigger is the potential distortion in the calculation of the persistence. For instance, if we add the 1950 break to the Spanish series, the only one absent from the UK chronology, the parameter of Spain behaves in a way very similar to that of the UK.

In the same way, Hsu (2005) tests for long memory when data have structural changes occurring at unknown dates. He proposed the modified local Whittle method to estimate the long-memory parameter (d) and the change point simultaneously. In addition, he uses Lavielle and Moulines's modified information criterion for long-memory data to estimate the number of breaks. The change-point estimates can locate on dates of two oil shocks. Analyzing monthly G7 inflation rates show that for Germany and Japan and for most G7 countries, the long-memory phenomenon is no longer significant (d<0,2) and may just be a consequence of structural changes. But for Italy and US, inflation rates still have strong dependence even when structural changes are allowed.

Recently, a literature has evolved documenting non-linearity in inflation, as seen in Henry and Shields (2003) work. The aim of this paper is to test for the existence of a unit root in inflation while explicitly allowing for non-linearity in the data. The paper employs bootstrap methods based on threshold autoregressive models to distinguish between non-linearity and/or non-stationarity. They applyied unit root tests (ADF, KPSS, DFGLS) and presented tests for non-linearity in the data, like BDS test which has the null hypothesis that u_t is independently and identically distributed and Granger and Terasvirta (1993) F -test of the null hypothesis of linearity.

The paper argues that standard unit root tests such as Dickey and Fuller (1981) and Elliot et al. (1996), and the KPSS tests of the null hypothesis of stationarity, may provide misleading evidence as to the degree of persistence of shocks to inflation. The source of the bias would appear to be the neglected non-linearity in the data. Considering quarterly inflation series based on consumer prices, for the US, Japan and the UK over the period 1960:I–2001:IV, they argue that popular tests of the unit root and stationary null hypotheses are based on misspecified regressions and provide misleading inference.

Unit root, stationarity, tests and problems

The last two decades a great deal of research has focused on the search for the best way to characterize or model the dynamic properties of economic and financial time series. Specifically the distinction between unit root and stationary processes has become a dominant topic in time series econometrics[4]. Nelson and Plosser's main achievement is to present statistical evidence that supports the hypothesis of a unit root in the autoregressive representations of a dozen macroeconomic time series for the US, including GNP, employment, wages, prices, interest rates, and stock prices. These results have significant implications for econometric modeling, for business cycle theorizing, and for economic policy prescriptions.

The presence or absence of unit roots, to put it simply, helps to identify some features of the underlying data generating process of a series. If a series has no unit roots, it is characterized as stationary, and therefore exhibits mean reversion in that it fluctuates around a constant long run mean. Also, the absence of unit roots implies that the series has a finite variance which does not depend on time (this point is crucial for economic forecasting), and that the effects of shocks dissipate over time.

[4] Nelson and Plosser (1982) were the first who published work on the existence of unit roots in macroeconomic time series

Stationarity

A process Y_t is stationary if the following conditions hold:

1. $E(Y_t) = m < \infty$ (Constant mean)

2. $Cov(Y_t, Y_{t-s}) = g_s < \infty$ (Depends on *s* but not on *t*)

Examples of Stationarity

- *White Noise*: the simplest form a time series process can take. The white note process is a zero mean, constant variance collection of random variables which are uncorrelated over time. More specifically, Y_t is a white noise process if $Y_t = e_t$

where:

a) $E(e_t) = 0$

b) $Var(e_t) = s^2$

c) $Cov(e_t, e_{t-s}) = 0$ for all $s, t \neq 0$

- *The zero mean first order autoregressive process* $AR(1)$: Y_t is a $AR(1)$ process with zero mean if

$$Y_t = fY_{t-1} + e_t$$

where e_t is a white noise process as defined above.

This process will be stationary if and only if $|f| < 1$.

Alternatively, if the series feature a unit root, they are better characterized as non-stationary processes that have no tendency to return to a long-run deterministic path. Besides, the variance of the series is time-dependent and goes to infinity as time approaches infinity, which results in serious problems for forecasting. Finally, non-stationary series suffer permanent effects from random shocks. As usually denominated in the literature, series with unit roots follow a *random walk*.

Non Stationary Processes

A non stationary process arises when one of the conditions for stationarity does not hold.

Examples of non stationarity

- The *determistic trend* process corresponds to:

$$Y_t = a + dt + u_t$$

where: ***a*** and ***d*** are parameters, ***t*** is a time index and u_t is any zero mean stationary process with variance s^2.
The deterministic trend process presents stationary fluctuations around a linear trend. The process is obviously non-stationary since its mean changes with time:

$$E(Y_t) = a + dt$$

Nevertheless, its variance is constant:

$$E(Y_t) = V(u_t) = s^2$$

Practically, our variable Y_t (inflation, GDP etc.) increases at a constant rate. By subtracting only dt from each observation (detrending), we can extract a stationary series. In this way the only difficulty is in identifying the trend.

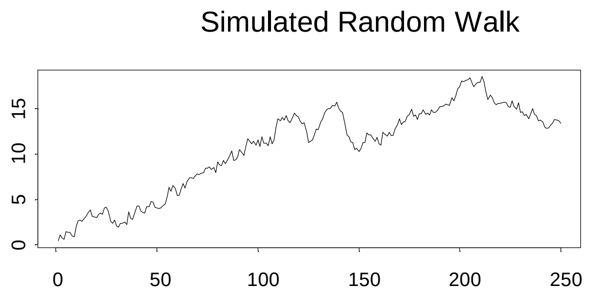
It would be relatively simple if macroeconomics had only a deterministic trend. But another common situation is one where the series is subject to shocks whose effects do not die away with time, that is *random walk* and *random walk with drift.*

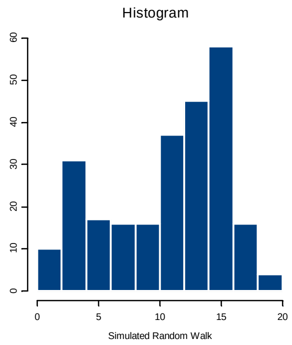
- The *random walk*

$$Y_t = Y_{t-1} + e_t$$

where e_t is a white noise process with variance s^2.Note that this is the zero mean AR(1) process with f = 1. It can be easily checked that $E(Y_t)$ = 0 and $V(Y_t)$= ts^2

In this case even though the mean of the process is constant, its variance is not, it grows unboundedly over time, so the process is not stationary.





- The *random walk with drift*

$$Y_t = m + Y_{t-1} + e_t$$

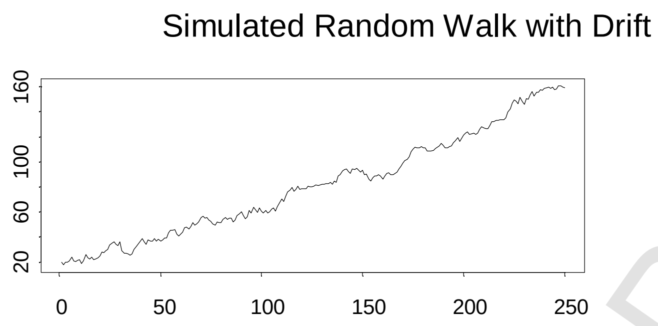
where m is a parameter known as the `drift' and e_t is a white noise process.

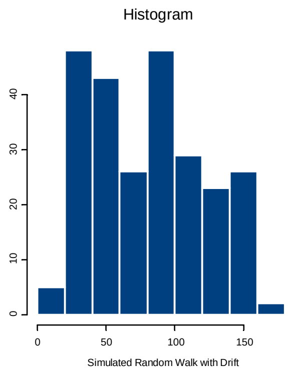
In this case, it can easily be proved that

$$E(Y_t) = tm$$

$$V(Y_t) = ts^2$$

Note that now both the mean and the variance grow over time.





Practically, macroeconomic variable each period is equal to its previous period's value plus an increase due to that period's innovations.

Unit Roots

The existence (or lack) of unit roots in macroeconomic time series brings about important implications, and this helps to explain why this topic has received a great amount of theoretical and applied research in the last two decades. There are many different issues in the unit roots literature that are somehow related but can be explored separately.

The problem of testing for unit roots (presence or absence of unit root) is likely to be the one of the most important and controversial topics in econometrics. If a series has no unit roots, it is characterized as stationary, and therefore exhibits mean reversion in that it fluctuates around a constant long run mean. Also, the absence of unit roots implies that the series has a finite variance which does not depend on time (this point is crucial for economic forecasting), and that the effects of shocks dissipate over time.

Alternatively, if the series feature a unit root, they are better characterized as non-stationary processes that have no tendency to return to a long-run deterministic path. Besides, the variance of the series is time-dependent and goes to infinity as time approaches infinity, which results in serious problems for forecasting. Finally, non-stationary series suffer permanent effects from random shocks. As usually denominated in the literature, series with unit roots follow a random walk.

In our simple framework testing for unit-roots means testing the hypothesis:

$$H_0 : f = 1 \qquad \text{Vs.} \qquad H_1 : |f| < 1$$

in the following general model:

$$Y_t = m + fY_{t-1} + dt + e_t$$

Taking in mind all the previous, we can conclude to the following table:

Case	Process	Parameters	Hypothesis about ϕ
1	AR(1)	$\|\phi\| < 1, d = 0$	Alternative
2	Deterministic Trend	$\|\phi\| < 1, d \neq 0$	Alternative
3	Random Walk	$\phi = 1, d = m = 0$	Null
4	Random Walk with drift	$\phi = 1, d = 0$	Null

In case 2, it is enough to remove time trend (detrending) so as to achieve stationarity (mean reverting) while random shocks would dissipate over time.

In case 3 and 4, stationariry cannot be achieved through detrending. There is no tendency for Y_t to return to a predetermined mean value, and its trajectory is given by an accumulation of disturbances (shocks). In other words, shocks seem to have permanent effect on the series.

To the question ***why do we care about unit roots in macroeconomics?*** we say that if a unit root is found, traditional estimation techniques cannot be used since spurious results are obtained when two variables with unit roots are regressed on each other: misleadingly high R squares and *t* statistics, and very low DW statistics. In that way, spurious regressions take place in cases where a significant relation is found when none really exists.

We can depict it in an example: Figure 1 plots the price level and rate of inflation in South Africa from 1980. It shows that South African prices have increased over time, but at a diminishing rate: inflation fell and then stabilised. Suppose you postulate that South African inflation is caused by world commodity prices. Figure 2 shows that a regression of South African prices on the Rand price of commodities yields a significant coefficient as predicted by your theory. But so does the spurious regression of South African consumer prices on the proportion of UK GDP accounted for by the service sector! The first seems plausible, the second does not. But in both cases you find a significant relationship. How are we to know whether the relationship between the South African price level and the Rand price of commodities is true or simply a spurious regression, as it is with UK GDP for service sector series?

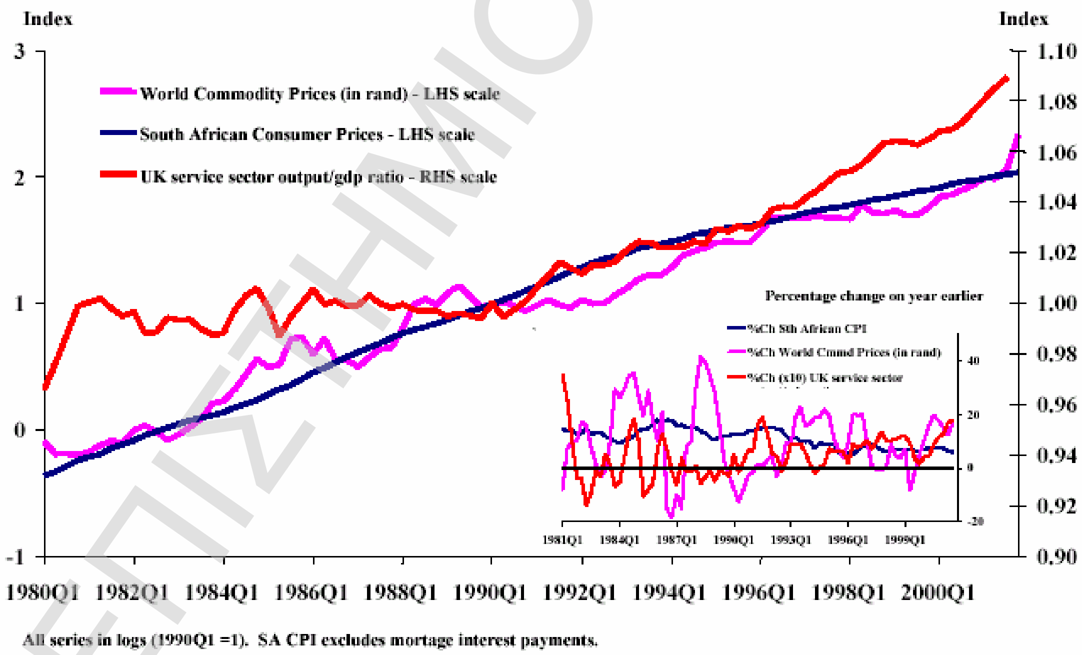


Figure 1: South African prices and inflation

Independent variable	Constant (t-stat)	Coefficient (t-stat)
WCP	-6.38 (-47.95)	1.07 (43.97)
(DW: 0.26, R^2: 0.96, No Obs.: 88)		
UKSERV	8.53 (14.69)	21.45 (15.71)
(DW: 0.05, R^2: 0.74, No Obs.: 88)		

Figure 2: Regressions 'explaining' South African inflation

A core issue for many central bank economists is to understand inflation and how its history can be used to help us forecast future inflation. The first step in such an investigation is to think about the economics, the institutional setting and so on. Once a clear framework is chosen it is important to investigate whether the data support your theoretical analysis. In order to forecast you need to obtain the coefficients for the model in some way, typically by estimation. To do this successfully you need to be confident that the estimation method you choose is appropriate.

To take it more practically, an understanding of the dynamic properties of the inflation rate is essential to policymakers' ability to keep inflation in check. Nonstationarity in the inflation process would have consequences for central banks' ratification of inflationary shocks and would affect macroeconomic policymakers' response to external pressures. Since forecasting performance improves significantly when the correct stochastic process is utilized for the series, utilizing the properties of ARFIMA representations may be able to make more accurate short and long-term forecasts of the future path of inflation rates, which are instrumental to the successful implementation of deflationary policies based on inflation targeting.

Unit Roots Tests

a) <u>*Dickey-Fuller test*</u> : $\Delta y_t = (a-1)y_{t-1} + u_t$,

A simple autoregressive variable has the form $y_t = ay_{t-1} + u_t$ Subtracting y_{t-1} from both sides gives Equation (1).

Equation (1) is the basis for the **Dickey-Fuller test**. The test statistic is the t-statistic on the lagged dependent variable. If $a > 1$, the coefficient on the lagged dependent variable will be positive. If α is unity, (α - 1) will equal zero. In both cases y_t will be non-stationary. The null hypothesis in the Dickey-Fuller test is that α equals 1. The alternative hypothesis is that α < 1, i.e. that (α -1) is negative, reflecting a stationary process. All we have to test for is whether the variable has a unit root, given that, in each case, we know what else determines the series.

McKinnon (1991, 1996) implements a much larger set of simulations than those given by Dickey and Fuller. Moreover, he estimates response surfaces for the simulation results, permitting the calculation of DF critical values and p-values for arbitrary sample sizes. It is McKinnon's values that are most commonly used now.

b) *Augmented Dickey-Fuller test (ADF):*

The presence of serial correlation in the residuals of the Dickey-Fuller test biases the results. For that reason the ADF test was developed. *The idea is to include enough lagged dependent variables to rid the residuals of serial correlation.*

The Augmented Dickey-Fuller test constructs a parametric correction for higher-order correlation by assuming that the y series follows an AR(p) process, and adds p lagged differences of y to the RHS of the test regression:

$$\Delta y_t = a y_{t-1} + b_1 \Delta y_{t-1} + ... + b_p \Delta y_{t-p} + u_t$$

This raises the problem of choosing the number of lags p. There are several ways of choosing how many lags need to be added. In practical terms, you'd like to add enough terms so that the errors are white noise. Tests for optimal lag lengths that are used include:

- Schwartz Information Criteria
- Akaike Information Criteria
- Hannan-Quinn Criteria
- Modified forms of these Criteria

You must also decide whether or not to include a time trend or constant term. Again the issue is to take all the information out of the residuals, to leave them white noise.

c) <u>*Phillips-Perron (PP) test:*</u>

Phillips and Perron (1988) is perhaps the most frequently used alternative to the ADF test. The Phillips-Perron (PP) test offers an alternative method for correcting for serial correlation in unit root testing. Basically, they use the standard DF or ADF test, but *modify the t-ratio so that the serial correlation does not affect the asymptotic distribution of the test statistic*. In the PP test, you have to decide whether or not to include a constant and/or time trend. You also have to choose a method for computing an estimator of the residual spectrum at frequency zero. This is often done by a sum-of-covariances approach or an autoregressive spectral density estimation. An advantage with the test is that it assumes no functional form for the error process of the variable (i.e. it is a ‘non-parametric’ test) which means that it is applicable to a very wide set of problems. A disadvantage for our purposes is that it relies on asymptotic theory. That means that in large samples the test has been shown to perform well. Unfortunately large samples are a rare luxury for monetary policy makers in any country and particularly in developing and transitional economies.

d) <u>*Ng and Perron (NP) Tests*</u>

Ng and Perron (2001) construct statistics that are based upon the GLS detrended data y_t^d . These test statistics are modified forms of Phillips and Perron Z_a and Z_t statistics

Size Distortion, Low Power, Inconsistency problems and structural breaks

- ***Low power***

Generally, when we refer to the power of a test, we mean the probability of rejecting the null hypothesis when is invalid. In a ADF or PP test, you face such problem if the trend that you chose to include is of higher degree than it is really necessary. In that way, reducing the power of the test means weakness to reject the null of a unit root. Unit root tests are often conducted after some kind of pre-test for the trend (regressor) which tests may be informal, such as inspection of time plots of the data. So it is easily perceivable that the probability to include shadowy trend regressor is very high.

Dickey (1984) demonstrated that :

> *if y_t is stationery about an intercept alone, then an inclusion of a linear time trend leads to a considerable loss of power.*

If we detrend a difference-stationary series the effects of errors will still be persistent. Essentially all that will have happened is that the errors will be de-meaned.

- ***Inconsistency***

This happens when the trend is of lower degree than is present. The problem that arises is that our test is always biased in favour of the null of unit root whether it really is or not. Commenting on this, West (1987) observes:

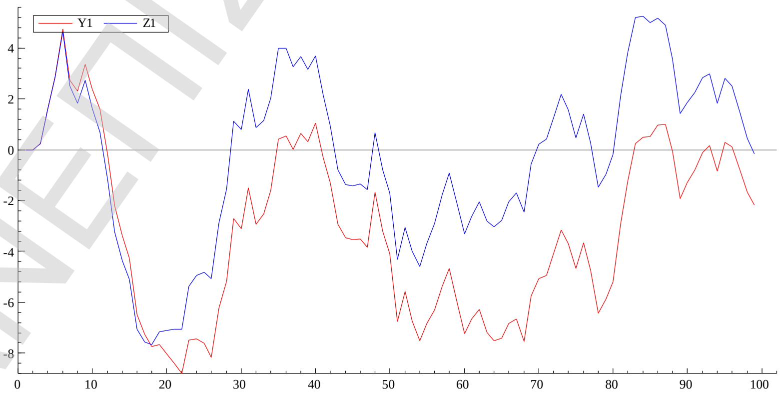
if y_t is stationary about a linear time trend but the trend is omitted from the regression mode, then asymptotically one never rejects a unit root

- ***Near unit root problem***

Unit root tests face low power problem in that they can not distinguish between Unit and near Unit Root. As seen in the diagram below, the problem starts when series is stationary but close to being unit root. Existence of such problem leads to low power of the test that is little probability of rejecting the null when it is invalid:

<u>*ex:*</u>

$$\left.\begin{aligned} & y_t = r y_{t-1} + u_t \\ & r = 0{,}95 \approx 1 \\ & H_0 = 1 \end{aligned}\right\} \quad H_0 \text{ is accepted}$$



Y is a unit root series

Z is a near-unit root series

- ***Size distortion***

Size distortion problem is inversely related to that of low power. Now the problem that we have to come up with is that our test tends to reject the null hypothesis when it is valid. Tests suffer from severe size distortions when the moving average polynomial of the first differenced series has a large negative root:

$$\text{ex:} \quad \left.\begin{array}{l} j = 1 \longrightarrow H_0 \text{ is correct: } y_t = y_{t-1} + u_t \\ u_t = e_t + J e_{t-1}, \quad J \sim \text{-}0{,}8 \end{array}\right\} \quad H_0 \text{ is rejected}$$

In this way, size distortion - low power problem are based on different conditions - one is based on a true and the other on a false null.

- ***structural breaks***

Another problem that arises is the omission to include structural breaks, where exist. In many cases time series in macroeconomics conclude to be Trend Stationary with St ructural Breaks[5], but neglecting the potential presence of structural changes leads Unit Root tests to be biased towards the Non Rejection of a Unit Root. Recent literature, however, connects fractional integration with structural breaks[6]

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[5] Perron (1989) argues that most macroeconomic variables are not unit root processes

[6] Gadea Sabaté and Serrano (2003), illustrate the risks of neglecting the potential presence of structural changes in economic series when estimating their long memory parameters

Solutions to the problems

To sum up, unit root tests face the problems of low power, size distortion and misspecification. Solution to such problems is found to modification on the ADF and PP tests that mentioned in the previous section.

I. <u>*Dickey-Fuller test with GLS detrending (DFGLS)*</u>:

This is an adaptation of the ADF test proposed by Elliott et al. (1996). In a ADF test regression, you may elect to include a constant, or a constant and a linear time trend. For these two cases, Elliott, Rothenberg and Stock (ERS) in 1996 propose a simple modification of the ADF tests in which the data are detrended using generalized least squares (GLS), so that explanatory variables are "taken out" of the data prior to running the test regression.. The DFGLS test involves estimating the standard ADF test equation, after substituting the GLS detrended $y_t{}^d$ for the original y_t (*GLS detrended data)*:

$$\Delta y^d{}_t = ay^d{}_{t-1} + b_1 \Delta y^d{}_{t-1} + ... + b_p \Delta y^d{}_{t-p} + u_t$$

In the paragraphs that will follow, we will try to show how this GLS technique of detrending y, works.

The augmented version of Dickey Fuller is based on the t-statistic for ρ=1, in the OLS regressions:

a. $\Delta y_t = (j-1)y_{t-1} + \sum_{j=1}^{r} a_j \Delta y_{t-j} + e_t$ (Neither trend nor constant included)

b. $\Delta y_t = (j-1)y_{t-1} + a_{00} + \sum_{j=1}^{r} a_j \Delta y_{t-j} + e_t$ (Only constant included)

c. $\Delta y_t = (j-1)y_{t-1} + a_{01} + a_{11}t + \sum_{j=1}^{r} a_j \Delta y_{t-j} + e_t$ (Both constant and trend included)

The test equations are being augmented with p lags of Δy_t, so as u_t to approximate a stationary AR(p).

The DF-GLS tests of Elliott et al. (1996) (ERS), differ from (a).-(c). in that we substitute y_t with $y_t^{\ d}$ in all the above test equations:

In which,

$$y_t^{\ d} = y_t, \quad \text{corresponding to (a)} \tag{1}$$

$$y_t^{\ d} = y_t - b_{00,GLS}, \quad \text{corresponding to (b)} \tag{2}$$

$$y_t^{\ d} = y_t - b_{01,GLS} - b_{11,GLS}, \quad \text{corresponding to (c)} \tag{3}$$

In that way, we succeed to extract the trend from our regression. The GLS test statistics are thus defined as the t-statistic on the coefficient of $y_{t-1}^{\ d}$ in the OLS regression of the newly created equations.

Estimation of operator $b_{ij,GLS}$

Writing $\bar{r}_j = 1 + \bar{c}_j / T, (j = 0,1)$, we can define the $b_{ij,GLS}$ as follows.

$\hat{b}_{00,GLS}$ is the OLS regression coefficient obtained by regressing the vector,

$$\begin{pmatrix} y_1 \\ y_2 - \bar{r}_0 y \\ \vdots \\ y_T - \bar{r}_0 y_{T-1} \end{pmatrix} \text{ on the vector, } \begin{pmatrix} 1 \\ 1-\bar{r}_0 \\ \vdots \\ 1-\bar{r}_0 \end{pmatrix}$$

Similarly, we find that $\left[\hat{b}_{01,GLS}, \hat{b}_{11,GLS}\right]'$ results from regressing the vector,

$$\begin{pmatrix} y_1 \\ y_2 - \bar{r}_1 y \\ \vdots \\ y_T - \bar{r}_1 y_{T-1} \end{pmatrix} \text{ on the vector, } \begin{pmatrix} 1 & 1-\bar{r}_1 & \cdots & 1-\bar{r}_1 \\ 1 & 2-\bar{r}_1 & \cdots & T-(T-1)\bar{r}_1 \end{pmatrix}$$

As the degree of any polynomial trend, that may be present in the data, is unknown, the objective of the testing strategy should be to *identify the class of model,* that is, to test the unit root and determine the trend degree.

Strategy

As the degree of any polynomial trend, that may be present in the data, is unknown, the objective of the testing strategy should be to *identify the class of model,* that is, to test the unit root and determine the trend degree. The steps of the strategy follow:

I. Perform a preliminary unit root test invariant to linear trend under the null.

II.(a) If the <u>unit root is not rejected</u> at step I, provisionally maintain this hypothesis and test for linear trend on the general maintained model $y_t = b_0 + b_1 t + u_t$, that is to test for $b_1 = o$

II.(b) If the unit root is rejected at step I, test for k=0 using the t-statistic

on a_{11}, that is to test if $a_{11} \neq 0$ in

$$\Delta y_t = (j-1) y_{t-1} + a_{01} + a_{11} t + \sum_{j=1}^{r} a_j \Delta y_{t-j} + e_t$$, equation

referred to standard tables, and stop.

III. If the unit root was not rejected at II(a**),** estimate

$$\Delta y_t = b^{*}_{00} + \sum_{j=1}^{r} a_j \Delta y_{t-j} + e_t$$, testing the null that k=0

using the t-statistic on b^{*}_{00}, that is to test if $b^{*}_{00} \neq 0$.

IIII.(a) If *k*=0 is rejected at step III, stop.

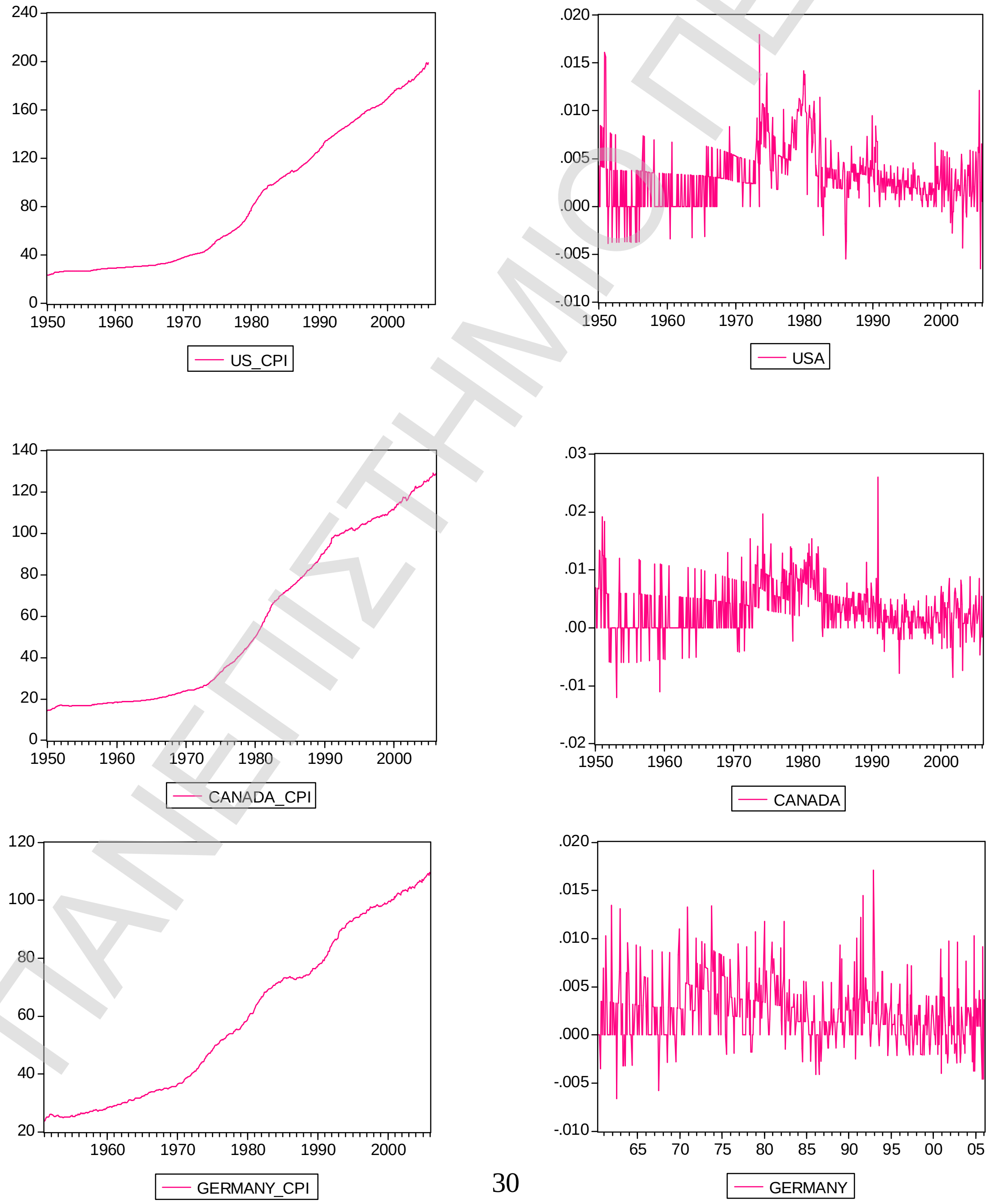
IIII.(b) If *k*=0 is accepted at step 4, conduct a further provisional unit root test invariant to the mean under the null.

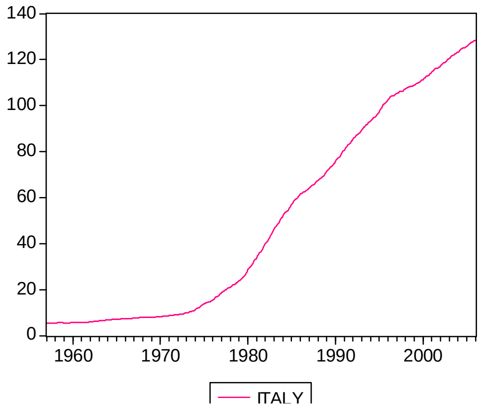
We applied the strategy in ADF-GLS of Elliott Rothenberg and Stock, in Phillips Perron and in Ng and Perron (NP) Tests

Analysis

In this section, our analysis is applied to the Usa, Canada, Germany, Italy, Uk, Japan, Greece, Eu and France inflation series covering the years 1950-2006, that is to say, we are considering the post war period.

CPIs - Inflation

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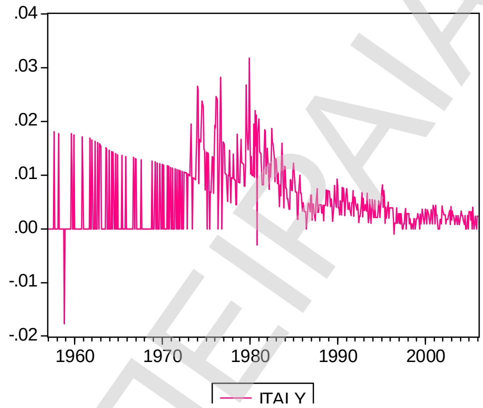
ITALY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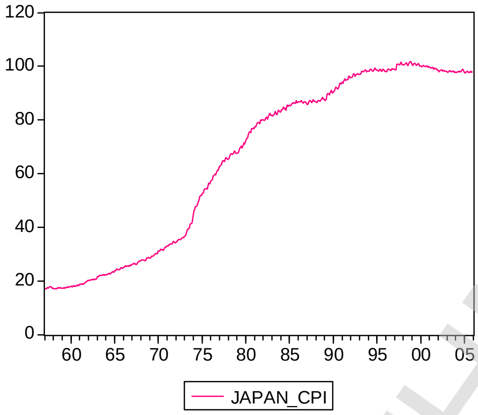
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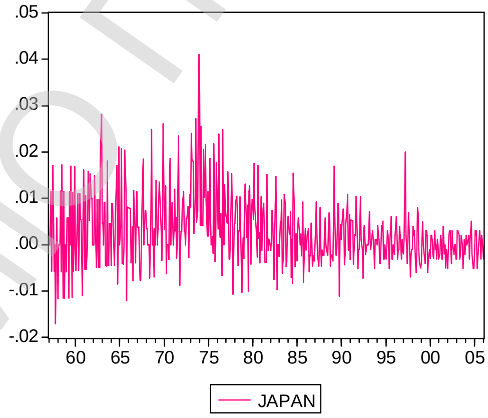
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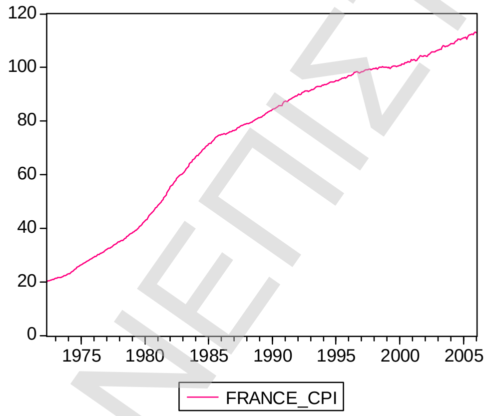
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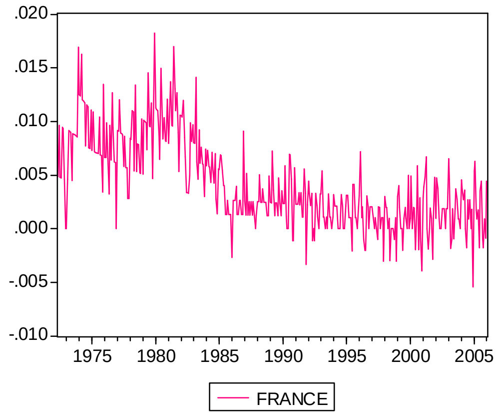
FRANCE_CPI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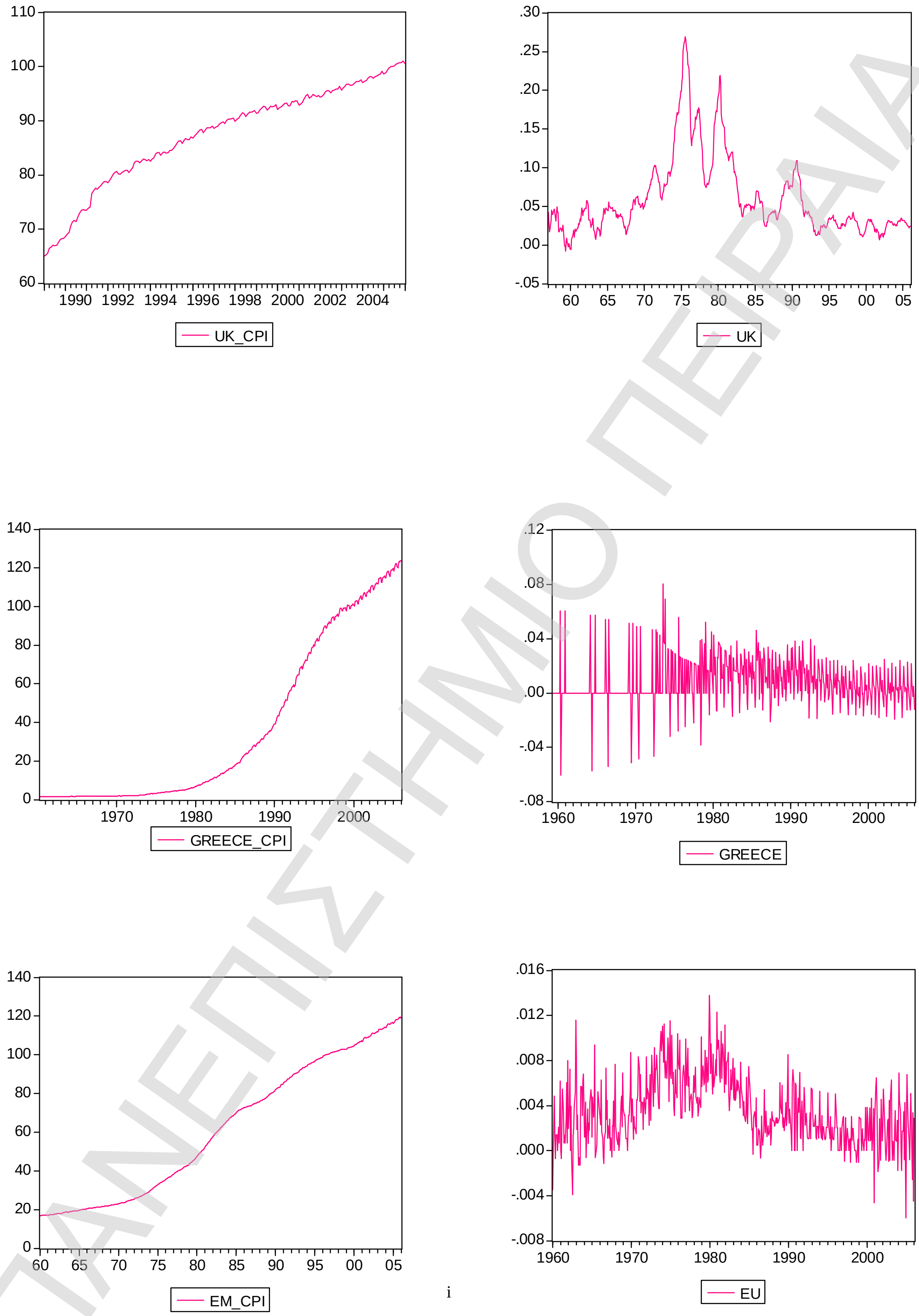
1975 1980 1985 1990 1995 2000 2005
FRANCE



i

[i] Figure 1: Graphs of CPIs and Inflations of. Base year for CPIs is different from country to country

In our analysis we have chosen to use a wide range of tests which, for the case of the unit root null hypothesis, include the traditional Dickey–Fuller (DF) and Phillips–Perron (PP) tests, ADF-GLS as well as that proposed recently by Perron and Ng (1996, 1998) and Ng and Perron (2001), which offers better qualities of size and power.

Unit root tests are often conducted after some kind of pre-test for the trend. Pre-tests may be very informal, such as inspection of time plots of the data. That's why we try to give a more formal side to the test so as to have more valid results. Based on that, we choose to use Ayat, and Burridge (2000) strategy in a way to provide a systematic resolution of the problem via evaluation of the significance of the trend.

1.1

The first results are set out in Table 1. We note that we took cases in unit root tests of including intercept and trend, intercept or none of them. As regards ADF test, we see that it accepts the null hypothesis (unit root) with respect to almost all of the countries and at all significant levels for all of the cases (intercept and trend-intercept-none). The reason why the result is the same for the three cases could be explained by the problems of low power and inconsistency that appear when we wrongly choose to include or not to include trend in our test.

Table 1: Applying ADF test on countries, in cases of a) Intercept and Trend, b) Intercept and c) None

ADF			
	Intercept+Trend	***Intercept***	***None***
	t-statistic (Prob.)	***t-statistic (Prob.)***	***t-statistic (Prob.)***
USA	**-2.884755 (0.1681)**	**-2.867914 (0.0497)****	**-1.874734 (0.058)***
CANADA	**-2.739809 (0.2208)**	**-2.741134 (0.0677)***	**-1.986474 (0.0451)****
GERMANY	**-4.206864 (0.0046)**	**-4.227491 (0.0006)***	**-2.749488 (0.0059)****
ITALY	**-2.171766 (0.5040)**	**-2.067511 (0.2582)**	**-1.301157 (0.1786)**
UK	**-1.969966 (0.6159)**	**-1.860218 (0.3513)**	**-1.208042 (0.2082)**
JAPAN	**-3.274356 (0.0716)***	**-2.467393 (0.1241)**	**-1.846804 (0.0618)***
GREECE	**-2.486362 (0.3349)**	**-2.562604 (0.1015)**	**-1.525661 (0.1193)**
EU	**16.1835 (0.6052)**	**-1.409274 (0.5786)**	**0.5786 (0.4132)**
FRANCE	**-3.736295 (0.0211)****	**-2.036878 (0.2710)**	**-1.548594 (0.1141)**

***reject null at 1%
**reject null at 5%
*reject null at 10%

Table 1give us results from ADF test, one of the most known unit root tests

Contradictory results are offered in the case of Phillips-Perron (PP) test. Contrary to the ADF test, PP test clearly reject the null hypothesis with respect to all the countries as it can be seen on *Table 2*. This difference in results between the two tests seems to be an outcome of the alternative method for correcting for serial correlation (non-parametric) in PP test in contrast with ADF test. In other words, the non parametric method of choosing trend degree is more reliable than that of ADF test. The only country where PP test doesn't reject unit root in inflation is Uk. And this is justifiable, as Uk had to face periods with high inflation, as one can see on the inflation graphs.

Table 2: Applying Phillips Perron (PP) test on countries, in cases of a) Intercept and Trend, b) Intercept and c) None of these

Phillips Perron (PP)			
	Intercept+Trend	***Intercept***	***None***
	t-statistic (Prob.)	***t-statistic (Prob.)***	***t-statistic (Prob.)***
USA	**-18.70373 (0)*****	**-19.03105 (0)*****	**-11.22820 (0)*****
CANADA	**-26.15005 (0)*****	**-26.15145 (0)*****	**-21.34016 (0)*****
GERMANY	**-21.33519 (0)*****	**-21.32161 (0)*****	**-22.05851 (0)*****
ITALY	**-19.84272 (0)*****	**-19.77862 (0)*****	**-12.88121 (0)*****
UK	**-2.436548 (0.3601)**	**-2.357845 (0.1544)***	**-1.583391 (0.1067)**
JAPAN	**-22.30651 (0)*****	**-22.87688 (0)*****	**-22.60581 (0)*****
GREECE	**-22.17769 (0)*****	**-22.16198 (0)*****	**-22.51433 (0)*****
EU	**-15.81489 (0)*****	**-15.70659 (0)*****	**-6.693914 (0)*****
FRANCE	**-14.46962 (0)*****	**-9.076813 (0)*****	**-5.117652 (0)*****

***reject null at 1%
**reject null at 5%
*reject null at 10%

Table 2 gives us results from Phillips Perron test, a non parametric test for correcting for serial correlation.

We used ADF-GLS test as an evolution of ADF which provides us with better power. In this test, taking in mind both the cases of intercept - trend and the case of intercept alone excluding the case of none of them as it has the same power with the conventional ADF test. The results show us that both in the case of intercept – trend and the case of intercept alone seem not to differentiate a lot from those of ADF test.

Table 3: Applying ADF-GLS test on countries, in cases of a) Intercept and Trend, b) Intercept and c) None of these

ADF-GLS

	Intercept+Trend	***Intercept***
	t-statistic (Prob.)	***t-statistic (Prob.)***
USA	**-2.725001 (0.0066)***	**-2.574743 (0.0103)*****
CANADA	**-2.213938 (0.0272)**	**-1.422189 (0.1555)**
GERMANY	**-1.817343 (0.0696)**	**-0.734348 (0.4630)**
ITALY	**-12.88121 (0.1060)**	**-1.366196 (0.1724)***
UK	**-1.797255 (0.0728)**	**-1.777400 (0.0760)**
JAPAN	**-2.042824 (0.0415)**	**-1.899928 (0.0580)***
GREECE	**-2.040862 (0.0417)**	**-1.587942 (0.1129)**
EU	**-0.763979 (0.4452)**	**-0.426155 (0.6702)**
FRANCE	**-2.598487 (0.0097)***	**-1.949172 (0.0520)****

***reject null at 1%
**reject null at 5%
*reject null at 10%

Table 3 gives us results from ADF-GLS unit root test, providing better power

Analyzing the results of Ng-Perron tests, we see that the majority of them do not reject unit root. Thereby, we conclude that these tests really give us better size by minimizing the cases where the tests tend to reject unit root hypothesis. Applying OLS regression to find if moving average polynomial of the first differenced series has a large negative root, as this is the reason of size distortion, we conclude that for many of the countries there is negative coefficient in MA(1). In this way, the results from this test seem to be more reliable.

Table 4: Operating Ng-Perron test (MZa-MZt) on countries, in cases of a) Intercept and Trend, b) Intercept and c) None of these

Ng-Perron[1]				
	MZa		*MZt*	
	Intercept + Trend	*Intercept*	*Intercept + Trend*	*Intercept*
	t-statistic	*t-statistic*	*t-statistic*	*t-statistic*
USA	**-9.87415**	**-8.87604****	**-2.20430**	**-2.04142****
CANADA	**-5.16433**	**-2.49236**	**-1.58643**	**-0.93162****
GERMANY	**-3.11578**	**-1.34470**	**-1.19877**	**-0.76765**
ITALY	**-3.93152**	**-2.90354**	**-1.37133**	**-1.19891**
UK	**-7.13222**	**-6.89311***	**-1.86795**	**-1.84776***
JAPAN	**-2.75894**	**-1.84600**	**-1.13707**	**-0.92419**
GREECE	**-1.32203**	**-1.37588**	**-0.66673**	**-0.76467**
EU	**-0.67275**	**-0.03405**	**-0.52610**	**-0.03980**
FRANCE	**-9.58715**	**-6.74889***	**-2.15971**	**-1.83623***

***reject null at 1%
**reject null at 5%
*reject null at 10%

Table 5: Operating Ng-Perron test (MZD-MPT) on countries, in cases of a) Intercept and Trend, b) Intercept and c) None of these

Ng Perron[2]				
	MSB		*MPT*	
	Intercept + Trend	*Intercept*	*Intercept + Trend*	*Intercept*
	t statistic	*t statistic*	*t statistic*	*t statistic*
USA	**0.22324**	**0.22999****	**9.31171**	**3.01812****
CANADA	**0.30719**	**0.37379**	**17.5649**	**8.96784**
GERMANY	**0.38474**	**0.57087**	**28.1006**	**16.8323**
ITALY	**0.34880**	**0.41291**	**22.8008**	**8.42359**
UK	**0.26190**	**0.26806***	**12.8132**	**3.58648***
JAPAN	**0.41214**	**0.50064**	**31.8650**	**12.8026**
GREECE	**0.50433**	**0.55577**	**51.0945**	**16.1835**
EU	**0.78201**	**1.16882**	**114.016**	**73.2785**
FRANCE	**0.22527**	**0.27208***	**9.63863**	**3.63293***

***reject null at significance level 1%
**reject null at significance level 5%
*reject null at significance level 10%

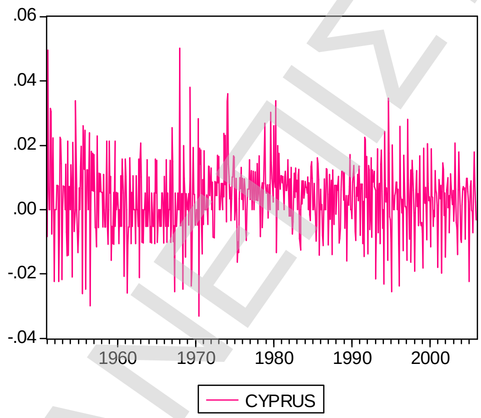
Tables 5&6 show results from Ng-perron tests, which provide us with better size

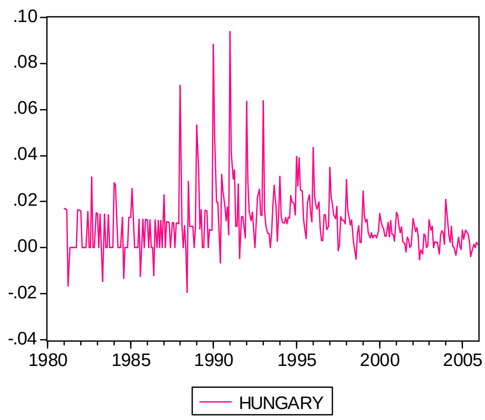
Summarizing, the tests of ADF and ADF-GLS, which give us no different results, lead us to say that the power of the test doesn't seem to increase using the improved way of estimating the degree of trend "parametrically". The results differentiate when we use Philips Perron. This is due to the non parametric method it uses to correct serial correlation in unit root testing. In our case, this test seems to be more reliable as in large samples the test has been shown to perform well.

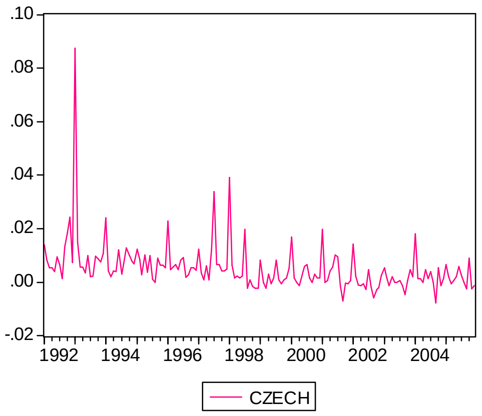
1.2

We choose to have a unit root analysis on the last ten new joined member countries in European Union, so as to have a comparison between the two groups of countries.

Inflation 10 New joined members of EU



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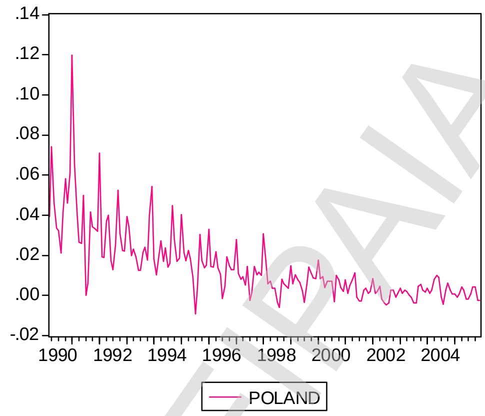
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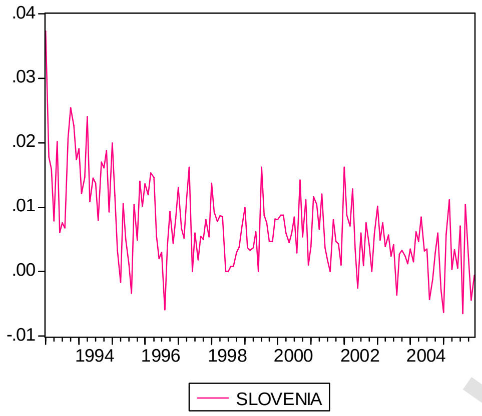
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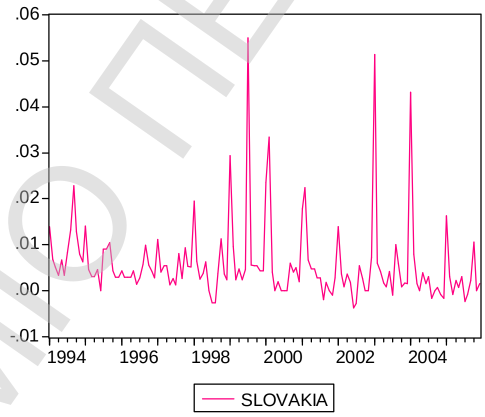
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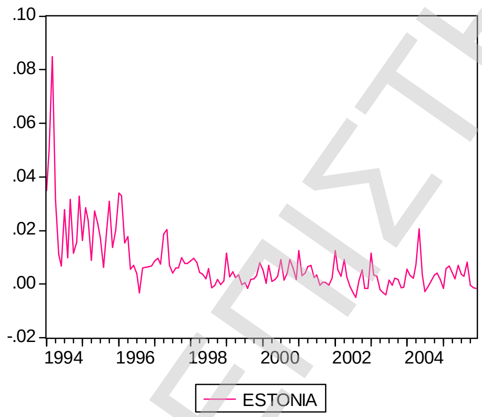
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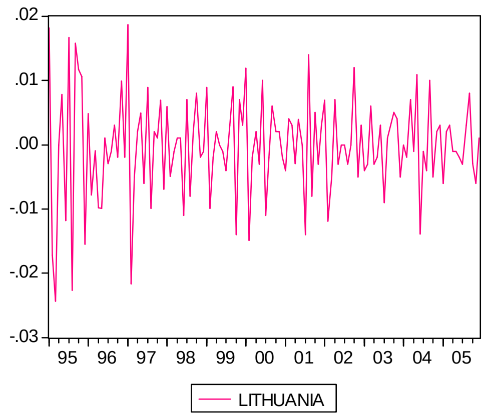
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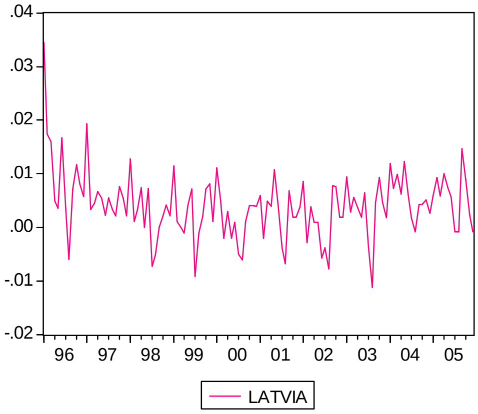
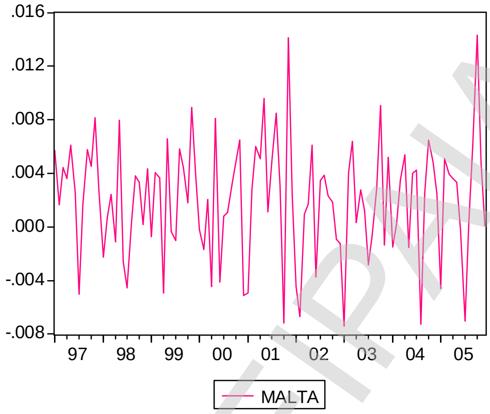
LITHUANIA





First we applied ADF test. The results seem to be the same for all three cases of included regressors. Except for Hungary case, in which the unit root hypothesis is supported, in all other cases the null, in general, is rejected. The rejection of the null in ADF test leads us to the conclusion that the test, in our situation, does not suffer from low power problem, as such kind of problem tends not to reject the null hypothesis.

Table 7: Applying ADF test on countries, in cases of a) Intercept and Trend, b) Intercept and c) None

ADF test results

	Intercept Trend	Intercept	None
Series	**Prob.**	**Prob**	**Prob**
CYPRUS	0.0007*	0.0000*	0.0025*
HUNGARY	0.9098	0.7387	0.4195
POLAND	0.0510	0.0199*	0.0002*
CZECH	0.0004*	0.3915	0.1025
SLOVENIA	0.0000*	0.0000*	0.0258*
ESTONIA	0.0093*	0.0374*	0.0088*
SLOVAKIA	0.0000*	0.0000*	0.0000*
LITHUANIA	0.0000*	0.0000*	0.0000*
LATVIA	0.0000*	0.0000*	0.0000*
MALTA	0.0000*	0.0000*	0.0000*

***Reject null hypothesis of unit root**

Table 7 shows the probability of accepting unit root hypothesis using ADF test. The test is applied on the ten new joined members of EU

In table 8, we can see that Philips Perron test rejects the unit root for almost all the series. This happens as a result of the non parametric selection of the lags. However, the results seems not to be reliable as in most of the series moving average polynomial of the first differenced has a large negative root, that is the reason for the problem of size distortion as we have already mentioned.

Table 8: Applying Phillips Perron (PP) test on countries, in cases of a) Intercept and Trend, b) Intercept and c) None of these

Phillips-Perron test results

	Intercept Trend	*Intercept*	*None*
Series	**Prob.**	**Prob.**	**Prob.**
CYPRUS	0.0000*	0.0000*	0.0000*
HUNGARY	0.0000*	0.0000*	0.0000*
POLAND	0.0000*	0.0000*	0.0000*
CZECH	0.0000*	0.0000*	0.0000*
SLOVENIA	0.0000*	0.0000*	0.0000*
ESTONIA	0.0000*	0.0000*	0.0000*
SLOVAKIA	0.0000*	0.0000*	0.0000*
LITHUANIA	0.0000*	0.0000*	0.0000*
LATVIA	0.0000*	0.0000*	0.0000*
MALTA	0.0000*	0.0000*	0.0000*

***Reject null hypothesis of unit root**

Table 8 shows the probability of accepting unit root hypothesis using PP test. The test is applied on the last ten joined members of EU

2.1

As we have already mentioned, we used the technique of ***L. Ayat, P. Burridge***[9] to provide a systematic resolution of inconsistency and low power problem via evaluation of the significance of the trend.

This technique could be implemented using any of the many forms of unit root test but in view of its good power, we illustrate its performance using the GLS form of the ADF, Phillips Perron test as well as the Ng Perron test in view of its good size.

First our analysis is applied to the Usa, Canada, Germany, Italy, Uk, Japan, Greece, Eu and France The first results are set out in Table 1. We can note that we took significance levels of 10% and 5% respectively. As regards ADF-GLS test, we see that for both significance levels, it rejects the unit root hypothesis for all of the countries. It only accepts the existence of intercept and trend for three of our countries. This comes in contradictory with the results of conventional ADF test. Taking in mind that the coefficient in the AR(1) is close to unity (near unit root problem) for many of our series we conclude that a test such ADF-GLS with good power give us reliable results, while the problem of size distortion still exists.

[9] L. Ayat, P. Burridge, 2000. Unit root tests in the presence of uncertainty about the non-stochastic trend

Table 1: Applying modified ADF-GLS test on countries, at significance levels of 10% and 5%

ADF-GLS								
	SIGNIF.LEV. 10%				SIGNIF.LEV. 5%			
	t-stat.	**C.V.**	**Unit root**	**intercept / trend**	**t-stat.**	**C.V.**	**unit root**	**intercept / trend**
USA	-8.6895	-1.98			-8.6895	-1.98		
CANADA	-8.03447	-1.98			-8.03447	-1.98		
GERMANY	-6.66879	-1.98			-6.66879	-1.98		
ITALY	-6.51022	-1.98			-6.51022	-1.98		
UK	-2.56869	-1.98			-2.55417	-1.98		
JAPAN	-10.1217	-2.91		**ü** / **ü**	-10.1217	-2.91		**ü** / **ü**
GREECE	-7.05468	-1.98			-7.05468	-1.98		
EU	-4.49736	-2.91		**ü** / **ü**	-4.49736	-2.91		**ü** / **ü**
FRANCE	-7.13664	-2.91		**ü** / **ü**	-7.13664	-2.91		**ü** / **ü**

Note: Modified ADF-GLS results do not give us unit root in our countries. They only support the hypothesis of intercept and trend for three of our series.

In the same way modified Phillips Perron test, in table 2, give us similar results. It supports intercept and trend for the same three countries while it rejects unit root for all of the series. Phillips Perron test, as we have already mentioned, via its technique of non parametric method for correcting for serial correlation provide better power to the test. This property, in relation with the resolution of inconsistency and low power problems that our modifications provide give us better results. This statement is reinforced from the fact that most of our series are near unit root, which is a low power problem cause.

Table 2: Applying modified Phillips Perron test on countries, at significance levels of 10% and 5%

Phillips Perron								
	SIGNIF.LEV. 10%				SIGNIF.LEV. 5%			
	t-stat.	C.V.	unit root	intercept / trend	t-stat.	C.V.	Unit root	intercept / trend
USA	-8.6895	-1.98			-8.6895	-1.98		
CANADA	-8.03446	-1.98			-8.03447	-1.98		
GERMANY	-6.66878	-1.98			-6.66879	-1.98		
ITALY	-6.51022	-1.98			-6.51022	-1.98		
UK	-2.56869	-1.98			-2.55417	-1.98		
JAPAN	-306.763	-17.3		**ü** / **ü**	-306.763	-17.3		**ü** / **ü**
GREECE	-7.05468	-1.98			-7.05468	-1.98		
EU	-44.6436	-17.3		**ü** / **ü**	-44.6436	-17.3		**ü** / **ü**
FRANCE	-115.812	-17.3		**ü** / **ü**	-115.812	-17.3		**ü** / **ü**

Note: Modified Phillips Perron results do not give us unit root in our countries. They only support the hypothesis of intercept and trend for three of our series.

In the tables that follow, the problem of size distortion seems to overcome. We applied the modified Ng Perron tests in our series. The results that we gained are identical to those from the previous tests, that is unit root is rejected and it supports intercept and trend for three of the countries. Ng Perron tests give us better size by minimizing the cases where the tests tend to reject unit root hypothesis. Taking in mind that in most of our countries the moving average polynomial of the first differenced series has a large negative root (see Appendix), we conclude that our results are plausible.

Table 3: Operating modified Ng-Perron test on countries, at significance level of 10%

Ng Perron

SIGNIF.LEV. 10%

	Mpt		**Mza**		**MSB**		**Mzt**			
	t-stat.	**C.V.**	**t-stat.**	**C.V.**	**t-stat.**	**C.V.**	**t-stat.**	**C.V.**	**unit root**	**intercept / trend**
USA	-8.69	-1.98	-8.69	-1.98	-8.69	-1.98	-8.69	-1.98		
CANADA	-8.03	-1.98	-8.03	-1.98	-8.03	-1.98	-8.03	-1.98		
GERMANY	-6.67	-1.98	-6.67	-1.98	-6.67	-1.98	-6.67	-1.98		
ITALY	-6.51	-1.98	-6.51	-1.98	-6.51	-1.98	-6.51	-1.98		
UK	-2.57	-1.98	-2.57	-1.98	-2.57	-1.98	-2.57	-1.98		
JAPAN	0.643	5.48	-142	-17.3	0.059	0.17	-8.43	-2.91		**ü / ü**
GREECE	-7.05	-1.98	-7.05	-1.98	-7.05	-1.98	-7.05	-1.98		
EU	2.888	5.48	-37.7	-17.3	0.113	0.17	-4.26	-2.91		**ü / ü**
FRANCE	1.125	5.48	-82.3	-17.3	0.078	0.17	-6.41	-2.91		**ü / ü**

Note: Modified Ng-Perron at 10% significance level results, do not give us unit root in our countries. They only support the hypothesis of intercept and trend for three of our series.

Table 4: Applying modified Ng-Perron test on countries, at significance level of 5%

Ng Perron

SIGNIF.LEV. 5%

	Mpt		Mza		MSB		Mzt			
	t-stat.	C.V.	t-stat.	C.V.	t-stat.	C.V.	t-stat.	C.V.	unit root	intercept / trend
USA	8.689	-1.98	-8.69	-1.98	-8.69	-1.98	-8.69	-1.98		
CANADA	-8.03	-1.98	-8.03	-1.98	-8.03	-1.98	-8.03	-1.98		
GERMANY	-6.67	-1.98	-6.67	-1.98	-6.67	-1.98	-6.67	-1.98		
ITALY	-6.51	-1.98	-6.51	-1.98	-6.51	-1.98	-6.51	-1.98		
UK	-2.55	-1.98	-2.55	-1.98	-2.55	-1.98	-2.55	-1.98		
JAPAN	0.643	5.48	-142	-17.3	0.059	0.17	-8.43	-2.91		**ü / ü**
GREECE	-7.05	-1.98	-7.05	-1.98	-7.05	-1.98	-7.05	-1.98		
EU	2.888	5.48	-37.7	-17.3	0.113	0.17	-4.26	-2.91		**ü / ü**
FRANCE	1.125	5.48	-82.3	-17.3	0.078	0.17	-6.41	-2.91		**ü / ü**

Note: Modified Ng-Perron at 5% significance level results, do not give us unit root in our countries. They only support the hypothesis of intercept and trend for three of our series.

2.2

We continue our analysis on the last ten new joined member countries in European Union. We can note first that via OLS regression for this set of countries, we found that our group is prone to size distortion problem more than to low power problem (see Appendix).

The first results are set in Table 5. We can note that, in contrast to the previous set of countries, the modified ADF-GLS test accepts unit root as well as intercept and trend for a significant number of our group of countries as much for 10% significance level as for 5%, while it accepts intercept and trend for some of the countries.

Table 5: Applying modified ADF-GLS test on ten new joined member countries in European Union, at significance levels of 10% and 5%

ADF-GLS								
			SIGNIF.LEV. 10%				SIGNIF.LEV. 5%	
	t-stat.	C.V.	unit root	intercept / trend	t-stat.	C.V.	unit root	intercept / trend
CYPRUS	-3.17	-1.98			-3.17	-1.98		
HUNGARY	-8.14	-1.98			-8.14	-1.98		
POLAND	-1.62	-2.91	ü	ü / ü	-0.98	-2.91		ü / ü
CZECH	-8.36	-2.91		ü / ü	-3.09	-2.91		ü / ü
ESTONIA	-5.07	-2.91		ü / ü	-5.07	-2.91		ü / ü
SLOVENIA	-0.68	-1.98	ü	ü / ü	-0.68	-1.98	ü	ü /
SLOVAKIA	-1.90	-1.98	ü	ü / ü	-1.90	-1.98	ü	
LITHUANIA	-4.86	-1.98			-4.86	-1.98		
LATVIA	-1.03	-1.98			-0.33	-1.98	ü	ü /
MALTA	-1.22	-1.98	ü		-1.22	-1.98	ü	

Note: Modified ADF-GLS results give us unit root for four of our countries. They also support the hypothesis of intercept and trend for five of our series.

Modified Phillips Perron test, in table 6, give us unit root for three countries and for four countries at 10% and at 5% respectively. In addition, it supports at least intercept for the eight of the ten countries. The good power that Phillips Perron test provides, doesn't seem to give better quality to our results as the OLS regression that we run give us MA(1) with large negative root (size distortion problem) for most of our series, than a close to unity coefficient in the AR(1) model (low power problem).

Table 6: Applying modified Phillips Perron test on ten new joined member countries in European Union, at significance levels of 10% and 5%

Phillips Perron

	SIGNIF.LEV. 10%				SIGNIF.LEV. 5%			
	t-stat.	C.V.	unit root	intercept / trend	t-stat.	C.V.	unit root	intercept / trend
CYPRUS	-3.17	-1.98			-3.17	-1.98		
HUNGARY	-8.14	-1.98			-8.14	-1.98		
POLAND	0.03	-17.3	ü	ü / ü	-0.76	-17.3	ü	ü / ü
CZECH	-147.97	-17.3		ü / ü	-82.33	-17.3		ü / ü
ESTONIA	-56.40	-17.3		ü / ü	-56.40	-17.3		ü / ü
SLOVENIA	-0.68	-1.98	ü	ü /	-0.68	-1.98	ü	ü /
SLOVAKIA	-1.27	-1.98		ü /	-1.27	-1.98	ü	
LITHUANIA	-37.65	-17.3		ü / ü	-37.65	-17.3		ü / ü
LATVIA	-1.03	-1.98	ü	ü /	-0.33	-1.98	ü	ü /
MALTA	-0.70	-1.98			-0.70	-1.98		ü /

Note: Modified Phillips Perron results give us unit root for three and four countries at significance level 10% and 5% respectively of our countries. They also support the hypothesis of intercept and trend for most of our series.

In table 7 and 8, we can see that Ng Perron tests results tend to accept null hypothesis of unit root, for four of the countries at significance level of 10% and for five countries at 5% significance level. Furthermore, it supports intercept and trend for a significant number of countries. The Ng Perron tests provide better results when size distortion exists. Such a problem that comes from large negative root in moving average is a problem that our group of countries does face as a whole. In that way, the results that come from this test should be taken seriously in mind.

Table 7: Applying modified Ng-Perron test on ten new joined member countries in European Union, at significance level of 10%

Ng Perron

SIGNIF.LEV. 10%

	Mpt t-stat.	C.V.	Mza t-stat.	C.V.	MSB t-stat.	C.V.	Mzt t-stat.	C.V.	unit root	intercept / trend
CYPRUS	-3.17	-1.98	-3.17	-1.98	-3.17	-1.98	-3.17	-1.98		
HUNGARY	-8.14	-1.98	-8.14	-1.98	-8.14	-1.98	-8.14	-1.98		
POLAND	530.05	5.48	0.17	-17.3	1.66	0.168	0.29	-2.91	ü	ü / ü
CZECH	1.16	5.48	-78.42	-17.3	0.08	0.168	-6.26	-2.91		ü / ü
ESTONIA	2.28	5.48	-40.52	-17.3	0.11	0.168	-4.49	-2.91		ü / ü
SLOVENIA	-0.68	-1.98	-0.68	-1.98	-0.68	-1.98	-0.68	-1.98	ü	ü /
SLOVAKIA	-1.90	-1.98	-1.90	-1.98	-1.90	-1.98	-1.90	-1.98		
LITHUANIA	-4.86	-1.98	-4.86	-1.98	-4.86	-1.98	-4.86	-1.98		
LATVIA	-1.03	-1.98	-1.03	-1.98	-1.03	-1.98	-1.03	-1.98	ü	ü / ü
MALTA	-1.22	-1.98	-1.22	-1.98	-1.22	-1.98	-1.22	-1.98	ü	

Note: Modified Ng-Perron at 10% significance level results, give us unit root for four of our countries. They also support the hypothesis of intercept and trend for two of our series and the hypothesis of intercept for two of our series.

Table 8: Applying modified Ng-Perron test on ten new joined member countries in European Union, at significance level of 5%

Ng Perron

SIGNIF.LEV.
5%

	Mpt t-stat.	C.V	Mza t-stat.	C.V	MSB t-stat.	C.V	Mzt t-stat.	C.V	unit root	intercept / trend
CYPRUS	-3.17	-1.98	-3.17	-1.98	-3.17	-1.98	-3.17	-1.98		
HUNGARY	-8.14	-1.98	-8.14	-1.98	-8.14	-1.98	-8.14	-1.98		
POLAND	98.96	5.48	-0.62	-17.3	0.72	0.168	-0.44	-2.91	**ü**	**ü** / **ü**
CZECH	-3.19	-1.98	-3.19	-1.98	-3.19	-1.98	-3.19	-1.98		
ESTONIA	2.28	2.283	-40.52	-17.3	0.11	0.168	-4.49	-2.91		**ü** / **ü**
SLOVENIA	-0.68	-1.98	-0.68	-1.98	-0.68	-1.98	-0.68	-1.98	**ü**	**ü** /
SLOVAKIA	-1.90	-1.98	-1.90	-1.98	-1.90	-1.98	-1.90	-1.98	**ü**	
LITHUANIA	-4.86	-1.98	-4.86	-1.98	-4.86	-1.98	-4.86	-1.98		
LATVIA	-0.33	-1.98	-0.33	-1.98	-0.33	-1.98	-0.33	-1.98	**ü**	**ü** /
MALTA	-1.22	-1.98	-1.22	-1.98	-1.22	-1.98	-1.22	-1.98	**ü**	

Note: Modified Ng-Perron at 5% significance level results, give us unit root for four of our countries. They also support the hypothesis of intercept and trend for two of our series and the hypothesis of intercept for two of our series.

Concluding remarks

We focused on the problems of inconsistency and low power which lead to contradictory results about unit root and inflation. In this way, we used the technique of ***L. Ayat, P. Burridge***[10] to provide a systematic resolution of such problems via evaluation of the significance of the trend. The objective of the testing strategy is to ***identify the class of model***, that is, to test the unit root and determine the trend degree in the inflation rates. We applied the strategy in ADF-GLS test, Phillips Perron and Ng and Perron (NP) Tests. In addition, we used the conventional tests of ADF, Phillips Perron, ADF-GLS of ERS and Ng Perron tests, in a way to compare the results of the two methods. As well, in view of comparison, we chose two set of countries inflation rates. G7 including Greece and the average of Eu countries is the first group and the ten new joined countries of European Union is the second.

The results that yielded using conventional test differentiate from those of modified tests. According to conventional tests, as far as the first group of countries is concerned, so much ADF, as ADF-GLS and Ng Perron tests seem to accept the hypothesis of unit root for the majority of the countries, while the Phillips Perron does not. In the second group of countries, unit root hypothesis seem to be rejected.

According to modified tests, the unit root hypothesis is rejected for all of the countries of the first group. The results are identical for all the applied tests. This is a sign that, in view of their good power that they provide the results are reliable. Contrary to the first group, modified

[10] L. Ayat, P. Burridge, 2000. Unit root tests in the presence of uncertainty about the non-stochastic trend

tests are different from test to test. The modified ADF-GLS test accepts unit root as well as intercept and trend for a significant number of our group. Modified Phillips Perron test give us unit root for the inflation of four countries. Ng Perron tests tend to accept null hypothesis of unit root for five countries. Knowing that Ng Perron tests give us better size, their results, in our case, seem more reliable as the 10 New joined members of European Union group is inclined to size distortion problem. This comes from the fact that the moving average polynomial of the first differenced series for most of the countries of the group has a large negative root (see Appendix).

Generally, using the new strategy of evaluation the class of the trend in the inflation rate, we can see that the results differentiate from those of conventional tests, providing us with better results about the behavior of countries inflation rate

Appendix

Dependent Variable: **Canada**
Method: Least Squares
Date: 05/28/06 Time: 18:48
Sample (Adjusted): 1950m02 2006m01
Included Observations: 672 After Adjustments
Convergence Achieved After 8 Iterations
Backcast: 1950m01

Variable	Coefficient	Std. Error	T-Statistic	Prob.
C	0.002844	0.001037	2.742794	0.0063
AR(1)	**0.982206**	**0.009343**	**105.1318**	**0.0000**
MA(1)	**-0.879545**	**0.024029**	**-36.60293**	**0.0000**

R-Squared	0.241832	Mean Dependent Var	0.003248
Adjusted R-Squared	0.239565	S.D. Dependent Var	0.004414
S.E. Of Regression	0.003849	Akaike Info Criterion	-8.277329
Sum Squared Resid	0.009913	Schwarz Criterion	-8.257194
Log Likelihood	2784.182	F-Statistic	106.6951
Durbin-Watson Stat	2.039239	Prob(F-Statistic)	0.000000

Inverted Ar Roots	.98
Inverted Ma Roots	.88

Dependent Variable: **USA**
Method: Least Squares
Date: 05/28/06 Time: 18:51
Sample (adjusted): 1950M02 2006M01
Included observations: 672 after adjustments
Convergence achieved after 10 iterations
Backcast: 1950M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003071	0.000779	3.944332	0.0001
AR(1)	**0.972388**	**0.011258**	**86.37628**	**0.0000**
MA(1)	**-0.779262**	**0.030103**	**-25.88661**	**0.0000**

R-squared	0.407113	Mean dependent var	0.003173
Adjusted R-squared	0.405341	S.D. dependent var	0.003251
S.E. of regression	0.002507	Akaike info criterion	-9.134916
Sum squared resid	0.004205	Schwarz criterion	-9.114781
Log likelihood	3072.332	F-statistic	229.6887
Durbin-Watson stat	1.812779	Prob(F-statistic)	0.000000

Inverted AR Roots	.97
Inverted MA Roots	.78

Dependent Variable: **UK**
Method: Least Squares
Date: 05/28/06 Time: 18:51
Sample (adjusted): 1957M02 2006M01
Included observations: 588 after adjustments
Convergence achieved after 9 iterations
Backcast: 1957M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.057082	0.029470	1.936917	0.0532
AR(1)	**0.989197**	**0.006190**	**159.7962**	**0.0000**
MA(1)	**0.305898**	**0.039568**	**7.731014**	**0.0000**

R-squared	0.986964	Mean dependent var	0.060296
Adjusted R-squared	0.986919	S.D. dependent var	0.051601
S.E. of regression	0.005902	Akaike info criterion	-7.422068
Sum squared resid	0.020375	Schwarz criterion	-7.399738
Log likelihood	2185.088	F-statistic	22144.79
Durbin-Watson stat	1.896571	Prob(F-statistic)	0.000000

Inverted AR Roots	.99
Inverted MA Roots	-.31

Dependent Variable: **JAPAN**
Method: Least Squares
Date: 05/28/06 Time: 18:51
Sample (adjusted): 1957M02 2006M01
Included observations: 588 after adjustments
Convergence achieved after 10 iterations
Backcast: 1957M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002953	0.000338	8.729084	0.0000
AR(1)	**-0.317053**	**0.171760**	**-1.845906**	**0.0654**
MA(1)	**0.507059**	**0.156079**	**3.248740**	**0.0012**

R-squared	0.038498	Mean dependent var	0.002956
Adjusted R-squared	0.035211	S.D. dependent var	0.007302
S.E. of regression	0.007172	Akaike info criterion	-7.032147
Sum squared resid	0.030092	Schwarz criterion	-7.009817
Log likelihood	2070.451	F-statistic	11.71159
Durbin-Watson stat	1.980424	Prob(F-statistic)	0.000010

Inverted AR Roots	-.32
Inverted MA Roots	-.51

Dependent Variable: **EU**
Method: Least Squares
Date: 05/28/06 Time: 18:49
Sample (adjusted): 1960M02 2006M01
Included observations: 552 after adjustments
Convergence achieved after 10 iterations
Backcast: 1960M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003545	0.001323	2.680269	0.0076
AR(1)	**0.990944**	**0.006560**	**151.0607**	**0.0000**
MA(1)	**-0.876029**	**0.022930**	**-38.20402**	**0.0000**

R-squared	0.424032	Mean dependent var	0.003533
Adjusted R-squared	0.421933	S.D. dependent var	0.002944
S.E. of regression	0.002238	Akaike info criterion	-9.360876
Sum squared resid	0.002750	Schwarz criterion	-9.337433
Log likelihood	2586.602	F-statistic	202.0887
Durbin-Watson stat	1.738542	Prob(F-statistic)	0.000000

Inverted AR Roots	.99
Inverted MA Roots	.88

Dependent Variable: **ITALY**
Method: Least Squares
Date: 05/28/06 Time: 18:50
Sample (adjusted): 1957M02 2006M01
Included observations: 588 after adjustments
Convergence achieved after 8 iterations
Backcast: 1957M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005545	0.002445	2.267820	0.0237
AR(1)	**0.989905**	**0.006723**	**147.2342**	**0.0000**
MA(1)	**-0.875272**	**0.023163**	**-37.78742**	**0.0000**

R-squared	0.407086	Mean dependent var	0.005362
Adjusted R-squared	0.405059	S.D. dependent var	0.006140
S.E. of regression	0.004736	Akaike info criterion	-7.862103
Sum squared resid	0.013122	Schwarz criterion	-7.839773
Log likelihood	2314.458	F-statistic	200.8259
Durbin-Watson stat	1.957134	Prob(F-statistic)	0.000000

Inverted AR Roots	.99
Inverted MA Roots	.88

Dependent Variable: **GERMANY**
Method: Least Squares
Date: 05/28/06 Time: 18:50
Sample (adjusted): 1951M02 2006M01
Included observations: 660 after adjustments
Convergence achieved after 9 iterations
Backcast: 1951M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002197	0.000234	9.377202	0.0000
AR(1)	**0.800624**	**0.064562**	**12.40084**	**0.0000**
MA(1)	**-0.692138**	**0.081304**	**-8.513022**	**0.0000**

R-squared	0.078547	Mean dependent var	0.002300
Adjusted R-squared	0.075742	S.D. dependent var	0.004021
S.E. of regression	0.003866	Akaike info criterion	-8.268756
Sum squared resid	0.009819	Schwarz criterion	-8.248337
Log likelihood	2731.689	F-statistic	28.00236
Durbin-Watson stat	1.886155	Prob(F-statistic)	0.000000

Inverted AR Roots	.80
Inverted MA Roots	.69

Dependent Variable: **GREECE**
Method: Least Squares
Date: 05/28/06 Time: 18:49
Sample (adjusted): 1959M02 2006M01
Included observations: 564 after adjustments
Convergence achieved after 22 iterations
Backcast: 1959M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007680	0.000737	10.42042	0.0000
AR(1)	**-0.482939**	**0.382064**	**-1.264027**	**0.2067**
MA(1)	**0.553721**	**0.363279**	**1.524231**	**0.1280**

R-squared	0.006333	Mean dependent var	0.007686
Adjusted R-squared	0.002790	S.D. dependent var	0.016734
S.E. of regression	0.016711	Akaike info criterion	-5.340227
Sum squared resid	0.156658	Schwarz criterion	-5.317168
Log likelihood	1508.944	F-statistic	1.787591
Durbin-Watson stat	1.999592	Prob(F-statistic)	0.168315

Inverted AR Roots	-.48
Inverted MA Roots	-.55

Dependent Variable: **FRANCE**
Method: Least Squares
Date: 05/28/06 Time: 18:50
Sample (adjusted): 1972M02 2006M01
Included observations: 408 after adjustments
Convergence achieved after 10 iterations
Backcast: 1972M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002563	0.003447	0.743452	0.4576
AR(1)	**0.993256**	**0.006583**	**150.8922**	**0.0000**
MA(1)	**-0.842356**	**0.028895**	**-29.15235**	**0.0000**

R-squared	0.607915	Mean dependent var	0.004216
Adjusted R-squared	0.605979	S.D. dependent var	0.004117
S.E. of regression	0.002584	Akaike info criterion	-9.071512
Sum squared resid	0.002705	Schwarz criterion	-9.042017
Log likelihood	1853.588	F-statistic	313.9697
Durbin-Watson stat	1.778899	Prob(F-statistic)	0.000000

Inverted AR Roots	.99
Inverted MA Roots	.84

Dependent Variable: **CYPRUS**
Method: Least Squares
Date: 06/07/06 Time: 10:48
Sample (adjusted): 1951M02 2005M12
Included observations: 659 after adjustments
Convergence achieved after 16 iterations
Backcast: 1951M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003558	0.000434	8.193654	0.0000
AR(1)	**-0.560544**	**0.227131**	**-2.467932**	**0.0138**
MA(1)	**0.597804**	**0.221724**	**2.696161**	**0.0072**

R-squared	0.014148	Mean dependent var	0.003564
Adjusted R-squared	0.011142	S.D. dependent var	0.010952
S.E. of regression	0.010891	Akaike info criterion	-6.197301
Sum squared resid	0.077804	Schwarz criterion	-6.176858
Log likelihood	2045.011	F-statistic	4.707190
Durbin-Watson stat	2.074696	Prob(F-statistic)	0.009337

Inverted AR Roots	-.56
Inverted MA Roots	-.60

Dependent Variable: **HUNGARY**
Method: Least Squares
Date: 06/07/06 Time: 10:51
Sample (adjusted): 1981M02 2005M12
Included observations: 299 after adjustments
Convergence achieved after 11 iterations
Backcast: 1981M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.010374	0.001291	8.035341	0.0000
AR(1)	**0.634144**	**0.126979**	**4.994096**	**0.0000**
MA(1)	**-0.360635**	**0.153031**	**-2.356615**	**0.0191**

R-squared	0.111166	Mean dependent var	0.010444
Adjusted R-squared	0.105160	S.D. dependent var	0.013472
S.E. of regression	0.012744	Akaike info criterion	-5.877566
Sum squared resid	0.048071	Schwarz criterion	-5.840438
Log likelihood	881.6961	F-statistic	18.51020
Durbin-Watson stat	1.973248	Prob(F-statistic)	0.000000

Inverted AR Roots	.63
Inverted MA Roots	.36

Dependent Variable: **POLAND**
Method: Least Squares
Date: 06/07/06 Time: 10:52
Sample (adjusted): 1990M02 2005M12
Included observations: 191 after adjustments
Convergence achieved after 9 iterations
Backcast: 1990M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.013661	0.001974	6.919062	0.0000
AR(1)	**0.354698**	**0.025441**	**13.94198**	**0.0000**
MA(1)	**0.292864**	**0.073618**	**3.978167**	**0.0001**

R-squared	0.636934	Mean dependent var	0.015357
Adjusted R-squared	0.633072	S.D. dependent var	0.022385
S.E. of regression	0.013560	Akaike info criterion	-5.747814
Sum squared resid	0.034568	Schwarz criterion	-5.696732
Log likelihood	551.9163	F-statistic	164.9063
Durbin-Watson stat	1.965619	Prob(F-statistic)	0.000000

Inverted AR Roots	.35
Inverted MA Roots	-.29

Dependent Variable: **CZECH**
Method: Least Squares
Date: 06/07/06 Time: 10:49
Sample (adjusted): 1992M02 2005M12
Included observations: 167 after adjustments
Convergence achieved after 65 iterations
Backcast: OFF (Roots of MA process too large)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002256	0.005369	-0.420232	0.6749
AR(1)	**0.985125**	**0.007478**	**131.7374**	**0.0000**
MA(1)	**-1.054928**	**0.035951**	**-29.34349**	**0.0000**

R-squared	0.204892	Mean dependent var	0.005141
Adjusted R-squared	0.195196	S.D. dependent var	0.009203
S.E. of regression	0.008256	Akaike info criterion	-6.738038
Sum squared resid	0.011178	Schwarz criterion	-6.682026
Log likelihood	565.6261	F-statistic	21.13070
Durbin-Watson stat	1.887710	Prob(F-statistic)	0.000000

Inverted AR Roots	.99
Inverted MA Roots	1.05

Dependent Variable: **SLOVENIA**
Method: Least Squares
Date: 06/07/06 Time: 10:53
Sample (adjusted): 1993M02 2005M12
Included observations: 155 after adjustments
Convergence achieved after 20 iterations
Backcast: 1993M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003079	0.001272	2.419521	0.0167
AR(1)	**0.978243**	**0.007453**	**131.2575**	**0.0000**
MA(1)	**-0.988067**	**0.005295**	**-186.5918**	**0.0000**

R-squared	0.326872	Mean dependent var	0.006872
Adjusted R-squared	0.318015	S.D. dependent var	0.006160
S.E. of regression	0.005087	Akaike info criterion	-7.704947
Sum squared resid	0.003934	Schwarz criterion	-7.646042
Log likelihood	600.1334	F-statistic	36.90578
Durbin-Watson stat	1.558354	Prob(F-statistic)	0.000000

Inverted AR Roots	.98
Inverted MA Roots	.99

Dependent Variable: **ESTONIA**
Method: Least Squares
Date: 06/07/06 Time: 10:50
Sample (adjusted): 1993M02 2005M12
Included observations: 155 after adjustments
Convergence achieved after 11 iterations
Backcast: 1993M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007175	0.004248	1.688942	0.0933
AR(1)	**0.917988**	**0.039533**	**23.22104**	**0.0000**
MA(1)	**-0.516092**	**0.088383**	**-5.839281**	**0.0000**

R-squared	0.532805	Mean dependent var	0.009133
Adjusted R-squared	0.526658	S.D. dependent var	0.012582
S.E. of regression	0.008656	Akaike info criterion	-6.641910
Sum squared resid	0.011389	Schwarz criterion	-6.583005
Log likelihood	517.7480	F-statistic	86.67304
Durbin-Watson stat	1.897247	Prob(F-statistic)	0.000000

Inverted AR Roots	.92
Inverted MA Roots	.52

Dependent Variable: **SLOVAKIA**
Method: Least Squares
Date: 06/07/06 Time: 10:53
Sample (adjusted): 1994M02 2005M12
Included observations: 143 after adjustments
Convergence achieved after 10 iterations
Backcast: 1994M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005784	0.000833	6.942627	0.0000
AR(1)	**-0.160963**	**0.416632**	**-0.386343**	**0.6998**
MA(1)	**0.340127**	**0.397907**	**0.854791**	**0.3941**

R-squared	0.031079	Mean dependent var	0.005775
Adjusted R-squared	0.017237	S.D. dependent var	0.008714
S.E. of regression	0.008638	Akaike info criterion	-6.644421
Sum squared resid	0.010447	Schwarz criterion	-6.582264
Log likelihood	478.0761	F-statistic	2.245306
Durbin-Watson stat	2.008807	Prob(F-statistic)	0.109695

Inverted AR Roots	-.16
Inverted MA Roots	-.34

Dependent Variable: **LITHUANIA**
Method: Least Squares
Date: 06/07/06 Time: 10:51
Sample (adjusted): 1995M02 2005M12
Included observations: 131 after adjustments
Convergence achieved after 18 iterations
Backcast: 1995M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000125	7.69E-05	-1.627626	0.1061
AR(1)	**0.398683**	**0.081779**	**4.875098**	**0.0000**
MA(1)	**-0.928929**	**0.025050**	**-37.08353**	**0.0000**

R-squared	0.301479	Mean dependent var	-0.000416
Adjusted R-squared	0.290565	S.D. dependent var	0.007711
S.E. of regression	0.006495	Akaike info criterion	-7.213052
Sum squared resid	0.005399	Schwarz criterion	-7.147208
Log likelihood	475.4549	F-statistic	27.62221
Durbin-Watson stat	2.150171	Prob(F-statistic)	0.000000

Inverted AR Roots	.40
Inverted MA Roots	.93

Dependent Variable: **LATVIA**
Method: Least Squares
Date: 06/07/06 Time: 10:51
Sample (adjusted): 1996M02 2005M12
Included observations: 119 after adjustments
Convergence achieved after 11 iterations
Backcast: 1996M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003509	0.000639	5.490100	0.0000
AR(1)	**0.525915**	**0.119144**	**4.414106**	**0.0000**
MA(1)	**-0.376434**	**0.153874**	**-2.446382**	**0.0159**

R-squared	0.117671	Mean dependent var	0.003799
Adjusted R-squared	0.102459	S.D. dependent var	0.005496
S.E. of regression	0.005207	Akaike info criterion	-7.652807
Sum squared resid	0.003145	Schwarz criterion	-7.582745
Log likelihood	458.3420	F-statistic	7.735149
Durbin-Watson stat	1.913063	Prob(F-statistic)	0.000702

Inverted AR Roots	.53
Inverted MA Roots	.38

Dependent Variable: **MALTA**
Method: Least Squares
Date: 06/07/06 Time: 10:52
Sample (adjusted): 1997M02 2005M12
Included observations: 107 after adjustments
Convergence achieved after 19 iterations
Backcast: 1997M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002007	0.000436	4.597373	0.0000
AR(1)	**-0.456691**	**0.787828**	**-0.579683**	**0.5634**
MA(1)	**0.509406**	**0.764911**	**0.665967**	**0.5069**

R-squared	0.004092	Mean dependent var	0.001995
Adjusted R-squared	-0.015061	S.D. dependent var	0.004330
S.E. of regression	0.004363	Akaike info criterion	-8.003866
Sum squared resid	0.001979	Schwarz criterion	-7.928927
Log likelihood	431.2068	F-statistic	0.213636
Durbin-Watson stat	2.097119	Prob(F-statistic)	0.807996

Inverted AR Roots	-.46
Inverted MA Roots	-.51

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