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Testing for Macroeconomic Convergence in Selected Countries

1. INTRODUCTION

The convergence hypothesis has been at the forefront of empirical growth research for over a decade. Convergence has been studied for over 10 years now in literally hundreds of studies. Whether income levels of poorer countries of the world are converging to those of richer countries is by itself a question of paramount importance for human welfare. This interest may be explained on two levels. First, the large contemporary differences in per capita incomes across countries have enormous welfare implications. As studies such as Bourguignon and Morrison (2002) and Firebaugh (1999) have argued, differences in per capita income across countries play a critical role in explaining levels of poverty and inequality across the world's population. Hence, to the extent that convergence occurs, it suggests that, at least over long time horizons, world inequality will diminish. Income convergence across countries is widely interpreted as a test of the Solow (1956) neoclassical growth model as opposed to the endogenous growth model pioneered by Lucas (1988) and Romer (1986); specifically, convergence tests have been used to evaluate the presence or absence of increasing returns to scale in the growth process.

The European economy has become more integrated in the last twenty-five years due to economic, political and institutional factors. Some key events in the resent history of Europe are the establishment of the Exchange Rate Mechanism in 1979, the opening of the Common Market in 1993 and the introduction of the Euro in 2001. These events, together with the worldwide increase in trade and financial flows, have led to a closer synchronization of economic fluctuations across European countries. It is therefore of particular interest to investigate whether the cyclical components of industrial production series, which are closely related to the business cycle, are evolving more closely over time as a result.

European union after growing in size from the original six members to twelve members and presently to fifteen member states is currently preparing for the biggest expansion ever in terms of scope and diversity. Of the thirteen countries that have applied to become members, ten countries are set to join the Union on May 1, 2004. These countries are Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, the Slovak Republic and Slovenia.

Since the early 1990s, the transition economies of Central and East Europe, the Baltic States, and of the former Soviet Union have introduced a series of fundamental economic reforms, allowing market forces to play a significant role in the decision-making process of economic agents. More recently, the countries have begun experiencing positive real economic growth.

Three reasons motivate us to investigate the degree of real convergence in transition economies. First, evidence of no economic convergence within a region can bring about social and political instability as economic performance varies significantly across countries. Second, the majority of the Central and Eastern European transition countries are also the first and second-round candidates for the European Union (EU). Finally, the majority of the countries have signed Association agreements with the EU. Evidence of non-convergence would imply that such institutional linkages with respect to the EU do not necessarily lead to macroeconomic convergence.

This paper addresses the issue of real income convergence between the ten accession candidates. Most accession candidates expect to join the EU soon (some as early as 2004), yet no specific economic conditions have been defined for the EU enlargement process. The “Copenhagen criteria” set out at the European Council's meeting in Copenhagen in June 1993 give three rather broad conditions.

- Stable institutions guaranteeing democracy, the rule of law, human rights and respect for the protection of minorities;
- A functioning market economy and capacity to cope with competitive pressures and market forces within the EU; and
- An ability to take on the obligations of membership, including adherence to the aims of political, economic and monetary union.

While these conditions lack quantitative economic targets, the last condition clearly implies that accession countries should be able to join Economic and Monetary Union (EMU). Most applicant states, however, see accession as full participation in all EU initiatives, including the euro. Therefore, from an economic perspective, all of these countries must apply considerable effort to satisfy the Maastricht convergence criteria as prerequisites to joining the euro area.

In light of future costs and benefits and the optimality of EU enlargement, it is arguable that real convergence or divergence is what matters. The greater the degree of real convergence, the smoother the future functioning of the enlarged EU. When less money is needed in the form of subsidies from the rich to the poor, more money will be available for structural adjustments to help harmonization of business cycles. Leaving aside the constructed indices for the quality of living, the ultimate benchmark for measuring convergence is the convergence in levels of real per capita income, real per capita GDP. However, as the GDP series for the accession countries is short we prefer to use the Industrial Production as a proxy to real GDP. The main reason for this choice is the availability of monthly data.

Brada and Kutan (2001) use cointegration tests on monthly data to study the convergence of money supply dynamics between transition economies and that of the EU approximated by Germany. They find mixed evidence with positive results for the Czech Republic, Estonia, Slovakia and Slovenia. Kočenda (1999) studies convergence among transition countries using monthly time-series on industrial output from 1991 to 1998. He also applies panel unit-root test as an econometric tool. His study finds limited evidence of convergence for some groups of countries, i.e. the Czech Republic, Poland and Hungary converge in the growth of industrial output.

Economic growth is the term economists use to describe the growth in output from an economy. Some economies achieve large increases in output over extended periods of time that, in turn, dramatically changes the economic, political and social landscape. Increasing output alone cannot be a sensible goal for any society. A more useful measure is the amount of output per person in the economy. When output per person (or GDP per capita) is high, people have more goods and services, and this may increase societal well-being.

Rogers (2002) in his paper outlined how modern economists think about the process of economic growth. The starting point is a consideration of the neoclassical growth model and "new", or endogenous, growth theory. The neoclassical growth model, originating with Solow (1956), has profoundly affected the way in which economists conceptualize long-run interrelationships between macroeconomies.

Neoclassical models

Convergence, the tendency of per capita income of different economies to equalize over time, is one of the predictions of Solow's neoclassical growth model. The Solow (1956) and Swan (1956) models are based on an aggregate production function of the form

$$Y = A\, f(K, L)$$

With output (*Y*) depending on capital (*K*), labour (*L*) and technology (*A*). If we assume growth in *L* and *A* are zero, growth in output will only occur if there is capital accumulation.

The level of output per worker when (net) capital accumulation stops is called the "steady state". As might be expected, as an economy approaches its steady state its rate of growth will decline.

If there is labour growth the outcome of the model is that output grows in proportion, hence output per worker is constant. If there is technology growth, this transmits directly to a positive, and equal, level of output per worker growth. An increase in *A* raises the marginal product of capital, which can be thought of as maintaining the incentive to invest.

The neoclassical models stress the accumulation of capital and the importance of (non) diminishing returns. Solow's model predicts that convergence exists among different economies regardless of initial conditions once the determinants of aggregate production functions are controlled for. It therefore requires a negative correlation between initial per capita output and its growth rate, so that poorer countries will catch up with wealthier countries.

Baumol (1986), Dowrick and Nguyen (1989), Wolff (1991), Barro and Xavier Sala-i-Martin (1991,1992), and Mankiw, Romer, and Weil (1992) conclude that economies do indeed converge. All of these studies reach their conclusions by examining the cross-sectional relationship between the growth rate of per capita output (or per worker) over some time period and the initial level of per capita output. This approach is valid only if economies have identical first-order autoregressive dynamic structures and all permanent cross-economy differences are completely controlled for.

Evans and Karras developed an alternative approach that is valid under much less restrictive conditions. Using their alternative approach, they found emphatic evidence that the 48 U.S. countries and the 54 countries, they used as sample, do in fact converge. They also found strong evidence that convergence is conditional rather than absolute for both samples.

Their empirical findings are consistent with neoclassical growth models, which predict convergence, and inconsistent with most endogenous growth models, which predict divergence.

The conventional approach attempts to infer whether and how economies converge by applying ordinary least squares to

$$g_n = a + b y_{n0} + g' x_n + n_n ,$$

where $g_n=(y_{nT} - y_{n0})/T$ is the average growth rate of per capita output for economy n between periods 0 and T, x_n is a vector of variables that control for permanent cross-economy differences in either levels or growth rates of per capita output, α and β are parameters, γ is a parameter vector, and v_n is an error term with a zero mean and finite variance. According to the above equation with $\beta < 0$, economies that are initially rich after controlling for the permanent differences associated with x_n and with any economy- specific effects in v_n grow more slowly than economies that are initially poor on the same basis. The convergence is absolute only if $\gamma = 0$ and conditional if $g \neq 0$.

The conventional approach produces invalid inferences unless their economies have identical first-order autoregressive dynamic structures and all permanent cross-economy differences in their per capita outputs are completely controlled for.

The alternative approach attempts to infer whether and how economies converge by applying the equation

$$\Delta(y_{nt} - \bar{y}_t) = d_n + r_n (y_{n,t-1} - \bar{y}_{t-1}) + \sum_{i=1}^{p} f_{ni} \Delta(y_{n,t-i} - \bar{y}_{t-i}) + u_{nt} ,$$

where r_n is negative if the economies converge and zero if they diverge, δ_n is a parameter, and the φs are parameters such that all roots of

$\sum_i f_{ni} L^i$ lie outside the unit circle. They assumed that *us* become uncorrelated as *N* approaches infinity.

According to Bernard and Durlauf (1995), empirical tests of convergence fall into two categories. The first class of tests studies the cross-section correlation between initial per capita output levels and subsequent growth rates for a group of countries. A negative correlation is taken as evidence of convergence as it implies that, on average, countries with low per capita initial incomes are growing faster than those with high initial per capita incomes.

A second set of tests has examined the long-run behavior of differences in per capita output across countries. Convergence, according to this approach, has the strong implication that output differences between two economies cannot contain unit roots or time trends and the weak implication that output levels in two economies must be cointegrated.

Endogenous growth models

In 1986 Paul Romer provided a model that yielded positive, long run growth rates without assuming exogenous technical change. Instead, Romer modeled technology growth as the outcome of competitive firms that invested in knowledge generation. The central idea that allowed this was that while individual firms face diminishing returns to investing in knowledge, at the societal level returns to knowledge could be increasing.

The model also suggests that a) the competitive growth rate is below the socially optimal level (due to the presence of knowledge externalities), b) large countries may grow faster (a scale effect), and c) shocks to a country's growth may have permanent effects.

Part of the endogenous growth achievement is to model imperfect competition (i.e. firms have some market power and set price above marginal cost). Technically, this is done by modeling an economy of symmetric firms that each has the monopoly right to a distinct good. In some models new goods are invented continuously (product variety models), while in others new goods displace older versions (creative destruction or product ladder models).

The need to model technology growth, and the search for models that yield positive long run growth, is the motivation for endogenous growth models.

A first problem is that empirical growth studies tend to conflate economic and statistical definitions of convergence.

Convergence as an economic phenomenon

Suppose that one observes two countries with identical preferences and technologies but with different initial human and physical capital stocks: convergence means that asymptotically, the growth rates in these economies will be identical. Barro (1997) describes the underlying economies of convergence as follows:

"The convergence property derives in the neoclassical model from the diminishing returns to capital. Economies that have less relative capital per worker (relative to their long-run capital per worker) tend to have higher rates of return and higher growth rates".

Malinvaud (1998) describes convergence as:

« ... countries or regions starting from very different levels of output per capita, evolving in stable environments and having access to the same technology should experience convergence: the dispersion of their output per capita should diminish; poor countries should grow faster than rich ones".

Formally, if $g_{i,t}$ denotes the growth in country i at time t, $S_{i,t}$ denotes the levels of human and physical capital, θ denotes technology, ρ denotes preferences, and $\mu(.)$ is a probability measure, then convergence can be thought of as the condition

$$\lim_{k \to \infty} m(g_{i,t+k} | S_{i,t}, q, r) \quad \textit{does not depend on } S_{i,t}$$

Convergence as a statistical phenomenon

The primary basis for empirical convergence studies has been cross-country growth regressions. Barro (1991), Barro and Sala-i-Martin (1992) and Mankiw, Romer and Weil (1992) are the seminal studies in this regard, although Kormendi and Meguire (1985) is an underappreciated antecedent. A canonical form for such regressions, is

$$g_i = y_{i,0}\, \beta + X_i\, \delta + Z_i\, \gamma + \varepsilon_I$$

where g_i is real per capita growth of country *i* across some fixed time interval, $y_{i,0}$ is the initial per capita income, X_i is a set of additional regressors suggested by the Solow growth model (population growth, technological change, physical and human capital savings rates transformed in ways implied by the model), Z_i is a set of additional control variables suggested by new growth theories, and ε_I is an error.

Variables such as initial income and population growth (as specified in the Solow model) affect growth because of their implications for transition dynamics towards a steady state. Variables such as saving rates reflect preferences and also affect short run dynamics. Other variables, in particular those one finds in Z_i , are usually interpreted as capturing differences in aggregate production functions across economies and as a proxy for growth theories that move beyond the Solow framework.

Following Barro (1991), Barro and Sala-i-Martin (1992) and Mankiw, Romer and Weil (1992), the economic notion of convergence is replaced in cross-country regressions studies with a particular statistical notion of conditional convergence. The above equation exhibits conditional β convergence if $\beta<0$.

Conditional β convergence means that if one observes two economies with identical X_i and Z_i values, the country with lower initial income will grow faster than the country with higher initial income.

Durlauf believes that there has been far too little attention paid to the question of heterogeneity in the growth experiences of different countries. Standard analyses fail to adequately deal with heterogeneity in the growth process. The role of factors such as geography or culture suggests that a common economic model is inadequate for describing the growth experiences across very diverse economies.

The use of growth regressions to interpret causal growth relationships requires strong homogeneity assumptions. For example, it is necessary to believe that the coefficients in the regression are constant across economies. Furthermore, following an argument in Brock and Durlauf (2001), it is necessary to believe that, the residuals are indistinguishable given a researcher's prior information about the countries with which the residuals are associated. A formal way to state this is that regression errors should exhibit a certain conditional exchangeability condition. Intuitively, one needs to believe that there is no prior reason why the residuals for one subgroup of countries should have a different mean than for some other subgroup.

Far greater effort should be made to the identification of subgroups of economies that can plausibly be described as obeying a common linear model. Operationally, this means that a primary goal of empirical work in growth should be the identification of sets of countries that appear to obey a common growth model. Once such groupings are achieved, a natural second step is the analysis of the factors that explain why a particular country is part of a particular grouping. This sort of approach will avoid the artificial idea that a negative relationship between initial income and growth is an appropriate way to think about convergence. The identification of subgroups of countries that obey a common growth model corresponds to the longstanding idea that there may be convergence clubs for aggregate economies.

Luginbuhl and Koopman (2003) defined convergence in terms of a decrease over time and modeled this decrease via mechanisms that allowed for gradual reductions in the ranks of covariance matrices associated with the disturbance vectors driving the unobserved components of the model.

The common converging component model was estimated for the per capita gross domestic product of five European countries. To investigate the existence of converging properties in economic time series Luginbuhl and Koopman adopted unobserved components time series (UC) models that typically consisted of interpretable components such as trend, cycle, seasonal and irregular components. Each component was separately modeled by an appropriate dynamic stochastic process, which usually depends on normally distributed disturbances.

The main contribution of this paper is the introduction of convergence mechanisms into the common trend-cycle model. At the beginning of the time series, for example, the vector cycle component is a linear function of three factors, and subsequently converges to being dependent on only two factors.

It is found that convergence features in trends and cycles are present and are associated with some key events in the history of European integration.

The following dichotomies indicate some of the different ways in which convergence has been understood:

a) Convergence *within* an economy vs. convergence *across* economies;
b) Convergence in terms of *growth rate* vs. Convergence in terms of *income level;*
c) β – convergence vs. σ – convergence ;
d) *Unconditional* (absolute) convergence vs. *conditional* convergence;
e) *Global* convergence vs. local or *club* – convergence; and

f) *Deterministic* convergence vs. *stochastic* convergence.

Convergence research has also witnessed the use of different methodologies, which may be classified broadly as follows:

a) Informal cross – section approach,
b) Formal cross – section approach,
c) Panel approach,
d) Time – series approach, and
e) Distribution approach.

The informal and formal cross – section approaches, the panel approach, and the time – series approach (in part) have all studied β – convergence, either conditional or unconditional. These approaches have generally dealt with convergence *across* economies and in terms of per capita income *level*. In addition, the formal cross – section approach and the panel approach have been used to study club – convergence and TFP – convergence. The cross – section approach has even been used to study σ–convergence. The time series approach has been used to investigate convergence both *within* an economy and *across* – economies. Finally, the distribution approach has gone beyond investigating just σ – convergence and has studied the entire shape of the distribution and intra – distribution dynamics. A useful way to start reviewing the convergence literature is therefore to provide a brief introduction to these different concepts of convergence.

The concept of conditional convergence is related with the notion of "club convergence". In the case of unconditional convergence, there is only one equilibrium–level to which *all* economies approach. In the case of conditional convergence, equilibrium differs by the economy, and each particular economy approaches its own but *unique* equilibrium. In contrast, the idea of club-convergence is based on models that yield *multiple* equilibrium.

Which of these different equilibrium an economy will reach, depends on its initial position or some other attribute. A group of countries may approach a particular equilibrium if they share the initial location or attribute corresponding to that equilibrium. This produces club- convergence.

From a chronological point of view, the study of convergence began with the notion of ‘absolute convergence’ and then moved to the concept of ‘conditional convergence.’ Both these concepts were initially studied using the notion of ‘β-convergence.’ The notion of σ-convergence arose later. Alongside emerged the concepts of ‘club-convergence,’ and the time series notions of convergence.

Several researchers, such as Bernard and Durlauf (1996), Carlino and Mills(1993), Evans (1996), and Evans and Karras (1996a), Li and Papell (1999), and others have investigated convergence using time series econometric methods. From this point of view, two economies, i and j, are said to converge if their per capita outputs, y_{it} and y_{jt} satisfy the following condition:

$$\lim_{k \to \infty} E(y_{i,t+k} - a y_{j,t+k} \mid \mathrm{I}_t) = 0$$

where I_t denotes the information set at time *t*.

This definition of convergence is relatively unambiguous for a two-economy situation. This is not so when convergence is considered in a sample of more than two economies. Researchers differ on defining convergence in such multi-country situations. Some have taken deviations from a reference economy as the measure of convergence. In this treatment, y_{it} in the above equation is replaced by y_{1t}, where 1 is the index for the reference country. Others have based their analysis of convergence on deviations from the sample average. In this treatment, y_{it} is replaced by $\bar{y}_t$ the average for time t. This difference is not innocuous, as we shall see. The time series definitions of convergence can be related with the notions of conditional and unconditional convergence too.

With a=1, the equation represents a variant of unconditional convergence. On the other hand, if $a \neq 1$ then the equation may represent a variant of conditional convergence. Within this framework a distinction has also been made between 'deterministic' and 'stochastic convergence'. This distinction refers to whether 'deterministic' or 'stochastic' trend is allowed in testing for unit root in the deviation series.

Convergence in terms of both growth rate and income level requires what is called β – convergence. This follows from the assumption of diminishing returns, which imply higher marginal productivity of capital in a capital – poor country. With similar savings rates, poorer economies will therefore grow *faster*. If this scenario holds, there should be a *negative* correlation between the initial income level and the subsequent growth rate. This led to the popular methodology of investigating convergence, namely running what is now known as the *growth-initial level* regressions. The coefficient of the initial income variable in these regressions (say, β) is supposed to pick up the negative correlation. Convergence judged by the sign of β is known as the β – convergence.

We observe *absolute β-convergence* when "poor economies tend to grow faster than rich ones". This definition assumes that all economies converge to the same steady-state level of per capita GDP.

The concept of *absolute β-convergence* in regression terms is given by

Equation 1 Absolute *β-convergence*

$$\gamma_{i,\,t,\,t+T} = a - b\,\log(y_{i,t}) + \varepsilon_{i,\,t+T} \quad ,$$

where b>0 means that there is convergence in the data set. The failure of many empirical studies to find *absolute β-convergence* leads, through the works of Barro and Sala-i-Martin (1992), and Mankiw, Romer, and Weil (1992) to a concept of *conditional β-convergence* whereby "the growth rate of an economy will be positively related to the distance that separates it from its own steady state." This concept reflects the fact that neither Solow's (1956) neoclassical growth model nor its optimal savings versions by Cass (1965) and Koopman (1965) imply convergence to the same steady state of per capita income. If economies have different technological and preference parameters, then nothing prevents them from converging to different steady states. Therefore, to investigate for the possibility of *conditional β-convergence,* one needs to include regression variables that determine the steady state:

Equation 2 *Conditional β-convergence*

$$\gamma_{i,\,t,\,t+T} = a - b\,\log(y_{i,t}) + \psi X_{i,t} + \varepsilon_{i,\,t+T} \quad ,$$

where $X_{i,t}$ is a vector of variables that hold constant the steady state of the economy *i*, and, as before, b>0 means that the data set exhibits *conditional β-convergence*.

However, such researchers as Quah (1993a), Friedman (1994), and others have emphasized that convergence is a proposition regarding *dispersion* of the cross-sectional distribution of income (and growth rate), and a negative *β* from the growth-initial level regression does not necessarily imply a reduction in this dispersion. According to this view, instead of judging indirectly and perhaps erroneously through the sign of *β*, convergence should be judged directly by looking at the dynamics of dispersion of income level and/or growth rate across countries. This gave rise to the concept of *σ* – convergence, where *σ* is the notation for standard deviation of the cross-sectional distribution of either income level or growth rate. While *β-convergence* reflects the movement of individual countries within a group, the concept of *σ – convergence* describes the evolution of income distribution of the entire group. Let σ_t be the time t standard deviation of log of real per capita GDP, then "a group of economies are converging in the sense of σ if the dispersion of their real per capita GDP levels tends to decrease over time. That is, if $\sigma_{t+T} < \sigma_t$".

Despite the limitations above, researchers have continued to be interested in β – convergence, in part because it is necessary, though not sufficient, condition of σ – convergence. The other reason is that methodologies, associated with investigation of β – convergence, also provide information regarding structural parameters of growth models, while research along the distribution approach usually do not provide such information.

The statistical notion of cointegration is well suited to study the co-movements of a set of variables in the long run. By definition, a set of possibly nonstationary variables are cointegrating if there exist linear combinations or cointegrating relations among them that are stationary and move together over time. The cointegrating relations have the appealing economic interpretation of long run equilibrium relationships among the variables under study. In general if there exist r cointegrating relations in a set of p variables, there must also exist $p - r$ common stochastic trends that move these variables around their equilibrium paths, and thus "drive" the cointegrating relations.

Koukouritakis and Michelis analyzed the long run cointegration properties of real per capita GDPs among the 10 new countries and the 3 EMU countries, France, Germany and the Netherlands. They viewed evidence of the long run co-movements in real per capita GDPs as strengthening the case for successful EMU enlargement by some or all the new countries.

According to Hall, Robertson and Wickens (1997) cointegration is not necessary for convergence as it is possible to construct series that are not cointegrated yet converge. For example, two series that differ by a random walk for t<T and are identical thereafter will converge in probability, and indeed pointwise, yet are not cointegrated. This brings out an important difference between the concepts of convergence and cointegration. Convergence is determined by the limiting (large t) behaviour of the series,

whilst cointegration is a property of the entire time history of the series. Discussions of convergence occur most naturally in the context of non-stationary series. In constructing a test for convergence it is important to take account of the distinction between convergence and cointegration.

Unit Root Analysis of Pooled Data for Countries

The time series analysis has been applied to investigate convergence across countries too. In fact, Evans and Karras (1996a) conduct a similar unit root analysis of pooled *deviation* (from average) data for a sample of 56 countries. The results favor rejection of unit root and by implication favor the conditional convergence hypothesis. Time series notions of convergence imply that per capita output disparities between converging economies follow a stationary process. Stochastic or deterministic convergence is therefore directly related to the unit root hypothesis in relative per capita output. Li and Papell utilized both conventional ADF tests as well as tests which incorporate a one-time break in the deterministic trend. Rejection of the null hypothesis of a unit root, whether or not a break is included, provides evidence of convergence. Li and Papell employed time series techniques that incorporate structural breaks to explore both deterministic and stochastic convergence among 16 OECD countries. In particular, they tested the unit root hypothesis on the log relative per capita output (to that of the group). If they found evidence against the unit root null for its relative per capita output, a country's output is converging to the aggregate output of the whole group. The unit root null is rejected in favor of trend stationarity, and hence evidence is provided for stochastic convergence. Incorporating trend breaks in the unit root tests significantly strengthens the findings of stochastic convergence.

Li and Papell found considerable evidence of convergence among the 16 OECD countries. Combining tests with and without structural breaks, they could reject the unit root null against an alternative of trend stationarity, and thus provide evidence for stochastic convergence, for 14 of the 16 countries. They could also reject the unit root null in favor of a level stationary alternative, and provide evidence of deterministic convergence, for 10 of the 16 countries. The results of the sequential unit root tests also reveal that World War II is the major cause for the structural shifts of relative per capita outputs.

Relationship to other convergence tests

Dispersion Methods

A method often used is to consider how the cross-section dispersion of a number of series behaves over time, after scaling the series appropriately, if necessary. Convergence is deemed to be occurring if the cross-section dispersion is declining over time. An important limitation of this approach is that it is not possible to use it if the underlying series are available only in index number form, for then the cross-section variance can be set arbitrarily at zero in any particular period by the choice of base period. In this way convergence at a given point in time can be guaranteed.

In practice there are a number of disadvantages to this measure. Constructing formal tests for convergence for this approach would involve delicate distributional assumptions and so detecting convergence remains a matter of judgement. The dispersion measure will not, in general, reveal which of the series has failed to converge. Moreover, if n is large and the length of time series is short, then the averaging inherent in the dispersion method will tend to obscure the contribution to the variance of any non-converging series.

Initial value regressions

This test is derived from the theory of growth and is based on the idea that rates of economic growth are mean reverting with the higher the growth rate, the lower the level of output (or output per capita), thus reducing disparities in growth rates over time.

This approach to the measurement of convergence involves testing for a negative relationship between the growth rates of a set of series and the initial level of the series, taken to imply that the cross-section dispersion declines over time. These initial value regressions do not necessarily imply that the cross-section dispersion diminishes over time, and thus has nothing to say about this mode of convergence.

An alternative approach would be to regress the growth rates on the lagged value of the level and test the significance of the regression coefficient of this lagged value. This, of course, is simply a test for the stationarity of the series. Under our definition of convergence any stationary series have converged. Thus, positive results from such tests will imply convergence. However such tests do not allow for convergence between non-stationary or trending variables, a case that we would not wish to rule out *a priori*.

Quah's Random Field Tests

Quah (1990b) uses the same definition of convergence that Hall, Robertson and Wickens propose, and relates convergence to cointegration. The concept of cointegration is modified to cope with the comparison of disparities among a set of series that are tested for stationarity. Whilst this comes closest to Hall, Robertson and Wickens' investigation, it is inherently a test of whether a set of series have converged, and cannot address the issue of whether such series are in the process of converging.

The plan of the paper is as follows. Section 2 provides definitions of convergence and common trends using a cointegration framework. Section 3 outlines the test statistics we use. Section 4 describes the data. Section 5 contains the empirical results.

2. CONVERGENCE IN STOCHASTIC ENVIRONMENTS

In our paper we test convergence in an explicitly stochastic framework. If long-run technological progress contains a stochastic trend, or unit root, then convergence implies that the permanent components in output are the same across countries. The theory of cointegration provides a natural setting for testing cross-country relationships in permanent output movements.

The organizing principles of our empirical work come from employing stochastic definitions for both long-term fluctuations and convergence. These definitions rely on the notions of unit roots and cointegration in time series.

We model the individual output series as satisfying

$$\alpha(L)\, Y_{i,t} = \mu_i + \varepsilon_{i,t}$$

where $\alpha(L)$ has one root on the unit circle and $\varepsilon_{i,t}$ is a mean zero stationary process. This formulation allows for both linear deterministic and stochastic trends in output. The interactions of both types of trends across countries can be formulated into general definitions of convergence and common trends.

Definition 2.1. Convergence in output

Countries j and i converge if the long-term forecasts of output for both countries are equal at a fixed time t:

$$\lim_{k \Rightarrow \infty} E(y_{i,t+k} - y_{j,t+k} \mid I_t) = 0$$

Definition 2.1'. Convergence in multivariate output

Countries p=1,....., n converge if the long-term forecasts of output for all countries are equal at a fixed time t:

$$\lim_{k \Rightarrow \infty} E(y_{1,t+k} - y_{p,t+k} \mid I_t) = 0 \qquad \forall\, p \neq 1$$

This definition of convergence asks whether the long-run forecasts of output differences tend to zero as the forecasting horizon tends to infinity. If $y_{1,t+k} - y_{p,t+k}$ is a mean zero stationary process then this definition of convergence will be satisfied. In order for countries *i* and *j* to converge under Definition 2.1 their outputs must be cointegrated with cointegrating vector [1, -1]. Additionally, if the output series are trend-stationary, then the definitions imply that the time trends for each country must be the same.

If countries do not converge in the sense of Definitions 2.1 or 2.1' they may still respond to the same long-run driving processes, i.e. they may face the same permanent shocks with different long-run weights.

Definition 2.2. Common trends in output

Countries i and j contain a common trend if the long-term forecasts of output are proportional at a fixed time t:

$$\lim_{k \Rightarrow \infty} E(y_{i,t+k} - \alpha y_{j,t+k} \mid I_t) = 0$$

Definition 2.2'. Common trends in multivariate output

Countries p= 1, ...,n contain a single common trend if the long term forecasts of output are proportional at a fixed time t, let $\bar{y}_t=[y_{2,t}\ y_{3,t}\ ....y_{p,t}]$

$$\lim_{k \Rightarrow \infty} E(y_{1,t+k} - \alpha'_p \bar{y}_{t+k} \mid I_t) = 0$$

Countries *i* and *j* have a common trend if their output series are cointegrated with cointegrating vector [1,-α]. This is a natural definition to employ if we are interested in the possibility that there are a small number of stochastic trends affecting output that differ in magnitude across countries.

Our analysis studies convergence by directly examining the time-series properties of various output series, which places the convergence hypothesis in an explicitly dynamic and stochastic environment.

3. OUTPUT RELATIONSHIPS ACROSS COUNTRIES

In order to test for convergence and common trends, we employ a multivariate technique developed by Johansen (1991, 1995a).

Let $y_{i,t}$ denote the output level (industrial production) of country *i* and $Dy_{i,t}$ the deviation of output in country *i* from output in country 1, i.e. $y_{1,t} - y_{i,t}$. Y_t is defined as the nx1 vector of the individual output levels, ΔY_t as the first difference of Y_t, DY_t as the (n-1)x1 vector of output deviations, $Dy_{i,t}$, and ΔDY_t the first differences of the deviations.

The starting point for the empirical work is the finding that the individual elements of the output vector are integrated of order one. A time series is said to be integrated of order *d*, in short, *I(d)*, if it has a stationary, invertible, non-deterministic ARMA representation after differencing *d* times. A non-stationary process is, by definition, one that violates the stationarity requirement, so its means and variances are non-constant over time.

To illustrate the use of Dickey-Fuller tests, we consider first an AR(1) process:

$$y_t = \mu + \rho y_{t-1} + \varepsilon_t \ ,$$

Where μ and ρ are parameters and ε_t is assumed to be white noise. *Y* is a stationary series if $-1 < \rho < 1$. If $\rho = 1$, *y* is a non-stationary series (a random walk with drift). If the process is started at some point, the variance of *y* increases steadily over time and goes to infinity. If the absolute value of ρ is greater than one, the series is explosive. Therefore, the hypothesis of a stationary series can be evaluated by testing whether the absolute value of ρ is strictly less than one. The DF test takes the unit root as the null hypothesis $H_0: \rho = 1$. Since explosive series do not make much economic sense, this null hypothesis is tested against the one-sided alternative $H_1: \rho < 1$.

The test is carried out by estimating an equation with y_{t-1} subtracted from both sides of the equation:

$$\Delta y_t = \mu + \gamma y_{t-1} + \varepsilon_t \quad ,$$

where $\gamma = \rho - 1$, and the null and alternative hypotheses are

H_0: $\gamma = 0$

H_1: $\gamma < 0$

The simple unit root test described above is valid only if the series is an AR(1) process. If the series is correlated at higher order lags, the assumption of white noise disturbances is violated. The ADF test makes a parametric correction for higher-order correlation by assuming that the *y* series follows an AR(p) process and adjusting the test methodology.

The ADF approach controls for higher-order correlation by adding lagged difference variable *y* to the right-hand side of the regression:

$$\Delta y_t = \mu + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \ldots + \delta_p \Delta y_{t-p} + \varepsilon_t$$

This augmented specification is then used to test:

H_0: $\gamma = 0$

H_1: $\gamma < 0$

in this regression.

When data are non-stationary purely due to unit roots, they can be brought back to stationarity by linear transformations, for example, by differencing, as in $y_t - y_{t-1} = \Delta y_t$. If $y_t \sim I(1)$, then by definition $\Delta y_t \sim I(0)$. An alternative is to try a linear transformation like $y_t - \beta_1 x_t - \beta_0 \sim I(0)$. But unlike differencing, there is no guarantee that $y_t - \beta_1 x_t - \beta_0$ is I(0) for any value of β.

The second natural step of the empirical work is to write a multivariate Wold representation of output as

$$\Delta Y_t = \mu + C(L)\varepsilon_t$$

Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary linear combination exists, it is called the *cointegration equation* and may be interpreted as a long-run equilibrium relationship among the variables. However, all variables must be integrated of the same order to be candidates to form a cointegrating relationship.

The purpose of the cointegration test is to determine whether a group of non-stationary series are cointegrated or not. The presence of a cointegrating relation forms the basis of the VEC specification. There are many possible tests for cointegration: the most general of them is the multivariate test based on the vector autoregressive representation (VAR) discussed in Johansen (1991, 1995a). Consider a VAR of order *p*

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + \varepsilon_t \qquad \text{with } \varepsilon_t \sim IN_p[0,\Omega_\varepsilon]$$

where y_t is a *k*-vector of non-stationary I(1) variables and ε_t is a vector of innovations. We can rewrite this VAR in the form of a VEC model as

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I \quad , \qquad \Gamma_i = -\sum_{j=i+1}^{p} A_j$$

Π represents the long-run relationship of the individual output series, while Γ_i traces out the short-run impact of shocks to the system.

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank $r < p$, then there exist $p \times r$ matrices α and β each with rank r such that $\Pi=\alpha\beta'$ and $\beta' y_t$ is I(0). The β coefficients characterize long-run relationships between levels of variables; the α coefficients describe changes that help restore an equilibrium market position. r is the number of cointegrating relations (the rank) and each column of β is the cointegrating vector. Cointegration vectors are of considerable interest when they exist, since they determine I(0) relations that hold between variables which are individually non-stationary. Such relations are often called “long-run equilibria”, since it can be proved that they act as “attractors” towards which convergence occurs.

However, β is not uniquely determined; a different choice of α satisfying equation $\Pi=\alpha\beta'$ will produce a different cointegrating matrix. Regardless of the normalization chosen, the rank of Π is still related to the number of cointegrating vectors. If the rank of Π equals p, then y_t is a stationary process. If the rank of Π is $0<r<p$, there are r cointegrating vectors for the individual series in y_t and hence the group of time series is being driven by p-r common shocks. If the rank of Π equals zero, there are p stochastic trends and the long-run output levels are not related across countries. In particular, from Definition 2.1, for the individual output series to converge there must be p-1 cointegrating vectors of the form (1, -1) or one common long-run trend. If there are n-r common trends among the n variables, there must be r cointegrating relationships. Note that $0< r< n$, since $r = 0$ implies that each series in the system is governed by a different stochastic trend and that $r = n$ implies that the series are $I(0)$ instead of $I(1)$. Convergence requires that the persistent parts be equal; common trends require that the persistent parts of individual output series be proportional. In a multivariate framework, proportionality and equality of the persistent parts corresponds to linear dependence.

Two test statistics proposed by Johansen to test the rank of the cointegrating matrix are derived from the eigenvalues of the MLE estimate of $\hat{\Pi}$. If $\hat{\Pi}$ is of full rank, p, then it will have no eigenvalues equal to zero. If, however, it is of less than full rank, $r < p$, then it will have p-r zero eigenvalues. Looking at the smallest p-r eigenvalues the statistics are

$$\text{Trace} = T\sum_{i=r+1}^{p} \hat{l}_i \approx -2\ln(Q;r,p) = -T\sum_{i=r+1}^{p}\ln(1-\hat{l}_i)$$

and

$$\text{maximum eigenvalue} = T\hat{l}_{r+1} \approx -2\ln(Q; r, r+1) = -T\ln(1-\hat{l}_{r+1})$$

The trace statistic tests the null hypothesis that the rank of the cointegrating matrix is *r* against the alternative that the rank is *p*. The maximum eigenvalue statistic tests the null hypothesis that the rank is *r* against the alternative that the rank is *r+1*. Critical values for the asymptotic distributions of both statistics are tabulated in Osterwald-Lenum (1992).

Five cases for trends and intercepts

The basic ideas are illustrated using the *p*-dimensional cointegrated VAR with a constant and a linear trend, but to simplify notations we assume that only one lag is needed, so $\Gamma_i = 0$. As before, $\varepsilon_t \sim IN_p[0,\Omega_\varepsilon]$:

$$\Delta y_t = \alpha\beta' y_{t-1} + \pi + \delta t + \varepsilon_t \qquad (1)$$

Without loss of generality, the two (px1) vectors π and δ can each be decomposed into two new vectors, of which one is related to the mean value of the cointegrating relations, $\beta' x_{t-1}$, and the other to growth rates in Δy_t:

$$\pi = \alpha\mu + \gamma \qquad (2)$$

$$\delta = \alpha\rho + \tau$$

Substituting (2) into (1) yields:

$$\Delta y_t = \alpha\beta' y_{t-1} + \alpha\mu + \gamma + \alpha\rho t + \tau t + \varepsilon_t$$

Thus, $\gamma \neq 0$ corresponds to constant growth in the variables x_t, whereas $\tau \neq 0$ corresponds to linear trends in growth, and so quadratic trends in the variables. Hence, the constant term and the deterministic linear trend play a dual role in the cointegrated model: in the α directions they describe a linear trend and an intercept in the steady-state relations; in the remaining directions, they describe quadratic and linear trends in the data.

We now discuss five of the most frequently used models arising from restricting the deterministic components in (1):

Case 1. **H(κ):** No restrictions on π and δ, so the trend and intercept is the VAR model. With unrestricted parameters, π, δ, the model is consistent with linear trends in the differenced series Δy_t and thus, quadratic trends in $y_{t.}$ Although quadratic trends may sometimes improve the fit within the sample, forecasting outside the sample is likely to produce implausible results. It is preferable to find out what induced the apparent quadratic growth and, if possible, increase the information set of the model.

Case 2. **H^*(κ):** τ = 0 but γ, μ, ρ remain unrestricted, so the trend is restricted to lie in the cointegration space, but the constant is unrestricted in the model. Thus, τ being zero still allows linear, but precludes quadratic, trends in the data. $E(\Delta y_t)=\gamma\neq 0$ implies linear deterministic trends in the level $y_{t.}$ When, in addition, $\rho\neq 0$, these linear trends in the variables do not cancel in the cointegrating relations, so the model contains 'trend-stationary' relations which can either describe a single trend-stationary variable, $(y_{1,t}-b_1 t)\sim I(0)$, or an equilibrium relation $(\beta_1' x_t - b_2 t)\sim I(0)$. Therefore, the hypothesis that a variable is trend-stationary can be tested in this model.

Case 3. **H_1(κ):** δ=0, so there are no linear trends in (1). Since the constant term π is unrestricted, there are still trends in the data, but no deterministic trends in any cointegration relations. Also, $E[\Delta y_t]= \gamma\neq 0$, is consistent with linear deterministic trends in the variables but, since ρ=0, these trends cancel in the cointegrating relations. $\pi\neq 0$ accounts for both linear trends in the DGP and a none-zero intercept in the cointegration relations.

Case 4. **H_1^*(κ):** δ=0, γ=0, but μ≠0, so the constant term is restricted to lie in the cointegration space. In this case, there are no linear deterministic trends in the data, consisted with $E[\Delta x_t] = 0$. The only deterministic components in the model are the intercepts in any cointegrating relations, implying that some equilibrium means are different from zero.

Case 5. **$H_2(\kappa)$:** $\delta=0$ and $\pi=0$, so the model excludes all deterministic components in the data, with both $E[\Delta y_t]=0$ and $E[\beta' y_t]=0$, implying no growth and zero intercepts in every cointegrating relation. Since an intercept is generally needed to account for the initial level of measurement, y_0, only in the exceptional case when the measurement start from zero, or when the measurements cancel in the cointegrating relations, can the restriction $\pi=0$ be justified.

When there are linear trends in the data, i.e. $E[\Delta y_t] \neq 0$, they can enter the model through the constant term, $\gamma \neq 0$ in $E[\Delta y_t] = \gamma + \tau t$ or through the cointegration relations, $\rho \neq 0$. Hence, given linear trends in the data, case 2 is the most general case. When the rank has been determined, it is always possible to test the hypothesis $\rho = 0$, as a linear restriction on the cointegrating relations.

If, on the other hand, $E[\Delta y_t]=0$, so there are no linear trends in the data, then the baseline model has the constant term restricted to the cointegration space, which is case 4 above. Therefore, based on the similarity argument, the rank should be based on either case 4 (trends in data) or case 2 (no trends in data). Nevertheless, if there is strong prior information that there are trends in the data, but they do not appear in the cointegration relations, then case 3 is the appropriate choice.

4. DATA

The data used in the empirical exercise are monthly, seasonally adjusted, log industrial production and most of them are obtained from the IFS CD-ROM. The countries involved are the 10 new countries and Germany, France and Netherlands, the 3 EMU countries.

These EMU countries serve as our benchmarks of EU policy and macroeconomic performance. Germany is the country traditionally used for this purpose in the convergence literature because of the alleged credibility of the policies of the Bundesbank and because it is the largest economy in the EU. Moreover, it is the largest trading partner of the transition economies. However, Germany experienced considerable monetary and real turbulence in the early and mid-1990s due to the difficulties encountered in the reunification of the country. Consequently, we also use France and Netherlands as a benchmark as they did not experience the adjustment costs that Germany did, and thus it may serve as a more stable indicator of EU policies and performance.

The sample is comprised of monthly data of varying time spans determined by data availability. The starting date for the data was January 1993, when the Czech and the Slovak Republic became independent states following the split of Czechoslovakia.

Due to lack of data availability, we dropped Malta from the sample.

We work with the logarithms of data in order to ensure positive outcomes and models with constant elasticities.

5. EMPIRICAL RESULTS ON CONVERGENCE

We first test for the presence of stochastic trends in each of the 12 output series. Table 1 presents the results for Augmented Dickey-Fuller tests.

Table 1

ADF tests on industrial production

COUNTRIES	SAMPLE	ADF TEST	UNIT ROOT	LAGS *P*
CYPRUS	1993:1-2003:12	- 2,483560	I(1)***	3
CZECH REPUBLIC	1993:1-2003:12	- 2,315681	I(1)***	1
ESTONIA	1993:1-2003:12	- 2,687872	I(1)***	3
HUNGARY	1993:1-2003:12	- 1,399327	I(1)***	2
LATVIA	1993:1-2003:12	- 3,763734	I(1)*	2
LITHUANIA	1993:1-2003:12	- 1,642817	I(1)***	4
POLAND	1993:1-2003:12	- 2,677709	I(1)***	3
SLOVAK REPUBLIC	1993:1-2003:12	- 1,964441	I(1)***	8
SLOVENIA	1993:1-2003:12	- 2,196603	I(1)***	0
FRANCE	1993:1-2003:12	- 1,389100	I(1)***	1
GERMANY	1993:1-2003:12	- 1,414383	I(1)***	2
NETHERLANDS	1993:1-2003:12	- 1,744809	I(1)***	3

* denotes statistical significance at the 1% level

** denotes statistical significance at the 5% level

*** denotes statistical significance at the 10% level

In order to select the appropriate lag length, we used the Modified Akaike's information criterion. As far as Latvia is concerned, the series of industrial production for this country is stationary (the ADF test exceeds only the test critical value of 1% and the probability of the test is 0,0217). However, according to the literature, Latvia is always taken as a non-stationary series and for this reason we will also consider it non-stationary. As a result, none of the 12 countries rejects the null hypothesis of a unit root in output.

Proceeding in a multivariate framework, choosing the sample period that was previously chosen (1993:M1 – 2003:M12), we examine the long run relationship among:

- the non-stationary series of the new EU countries
- the non-stationary series of the new EU countries plus the industrial production series of Germany, France and Netherlands

In the first sample we dropped off Lithuania and Estonia. This happened as we run a cross-country model and there should be a common sample period so that our estimations would not be affected.

In the second sample we dropped off Lithuania and Estonia as the data spans for these countries were very small.

To select the appropriate lag length, ρ, we set up a separate VECM for each group and use the likelihood ratio test to carry out hypothesis testing. Under the hypothesis $\Gamma_\rho = 0$, the likelihood ratio test is asymptotically distributed as χ^2 with p^2 degrees of freedom.

For the group of the seven new countries of the EU the lag length that we found was $\rho=1$.

Table 2

Lag selection for the 7 new EU countries

VAR Lag Order Selection Criteria

Endogenous variables: DCYP DCZ DHUN DLAT DPOL DSLVK DSLVN

Exogenous variables: C

Date: 06/22/04 Time: 21:31

Sample: 1993:01 2003:12

Included observations: 121

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1865.404	NA	1.08E-22	-30.71743	-30.55569*	-30.65174
1	1963.206	182.6711	4.81E-23*	-31.52407*	-30.23015	-30.99856*
2	2007.540	77.67666	5.24E-23	-31.44695	-29.02085	-30.46162
3	2048.701	67.35333	6.08E-23	-31.31737	-27.75909	-29.87222
4	2092.608	66.76747	6.87E-23	-31.23318	-26.54273	-29.32821
5	2128.198	50.00305	9.14E-23	-31.01154	-25.18890	-28.64674
6	2169.227	52.89657	1.15E-22	-30.87978	-23.92496	-28.05517
7	2228.117	69.11120*	1.12E-22	-31.04326	-22.95626	-27.75882
8	2287.772	63.10555	1.15E-22	-31.21937	-22.00019	-27.47511

* indicates lag order selected by the criterion

Furthermore, for the group of the seven new countries and the three countries of the EMU the lag length was $\rho = 1$.

Table 3

Lag selection for the 7 new and the 3 EMU countries

VAR Lag Order Selection Criteria

Endogenous variables: DCYP DCZ DFR DGER DHUN DLAT DNETH DPOL DSLVK DSLVN

Exogenous variables: C

Date: 06/24/04 Time: 20:29

Sample: 1993:01 2003:12

Included observations: 121

Lag	LogL	LR	FPE	AIC	SC	HQ
0	2909.962	NA	7.21E-34	-47.93325	-47.70220*	-47.83941
1	3073.359	297.0864	2.54E-34*	-48.98115	-46.43952	-47.94890*
2	3167.032	154.8312	2.91E-34	-48.87657	-44.02437	-46.90590
3	3250.959	124.8500	4.12E-34	-48.61090	-41.44813	-45.70182
4	3349.463	130.2531	4.96E-34	-48.58617	-39.11283	-44.73868
5	3447.103	112.9717	6.84E-34	-48.54716	-36.76325	-43.76126
6	3535.610	87.77516	1.30E-33	-48.35718	-34.26270	-42.63288
7	3687.989	125.9336*	1.11E-33	-49.22296	-32.81791	-42.56024
8	3842.121	101.9055	1.34E-33	-50.11771*	-31.40208	-42.51658

* indicates lag order selected by the criterion

Further, to determine which submodel describes best each set of variables, we test the various submodels against each other using likelihood ratio tests in Johansen (1995), which are also distributed as χ^2 with appropriate degrees of freedom. The degrees of freedom for testing pairs of the five nested submodels, which are nested from the most to the least restrictive, are defined as follows:

$$H_2(\kappa) \underset{r}{\subset} H_1^*(\kappa) \underset{p-r}{\subset} H_1(\kappa) \underset{r}{\subset} H^*(\kappa) \underset{p-r}{\subset} H(\kappa)$$

Johansen (1995) constructed likelihood ratio tests in order to choose between the different deterministic trend specifications of cointegration, for given *κ* cointegrating vectors. These likelihood ratio tests are the following:

$$-2\log Q(H_2(\kappa) \,|\, H_1^*(k)) = T\sum_{i=1}^{k}\log(1-\hat{l}_i)/(1-l_i^*) \square\ c^2(k)$$

$$-2\log Q(H_1(\kappa) \,|\, H^*(k)) = T\sum_{i=1}^{k}\log(1-\hat{l}_i)/(1-l_i^*) \square\ c^2(k)$$

$$-2\log Q(H_1^*(\kappa) \,|\, H_1(k)) = T\sum_{i=k+1}^{n}\log(1-\hat{l}_i)/(1-l_i^*) \square\ c^2(n-k)$$

$$-2\log Q(H^*(\kappa) \,|\, H(k)) = T\sum_{i=k+1}^{n}\log(1-\hat{l}_i)/(1-l_i^*) \square\ c^2(n-k)$$

where $\hat{l}_i$ and l_i^* are the i greater eigenvalues under the hypothesis H and H^* respectively. This test is conducted as follows: we start from the most restrictive case and turning down the hypothesis consecutively we move on to the less restrictive case. When a certain test is accepted, we accept this hypothesis.

For the group of the seven new countries of the EU the deterministic trend specification of cointegration that was chosen was case 3: H_1, which allows for linear trend in data (Intercept (no trend) in CE and VAR).

Table 4

Choise of the appropriate model for the cointegration test

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or	No Intercept	Intercept	Intercept	Intercept	Intercept
No. of CEs	No Trend	No Trend	No Trend	Trend	Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	2	4	2	1	2
Max-Eig	2	1	1	1	1
0	2005.124	2005.124	2020.35	2020.35	2022.404
1	2030.865	2031.004	2044.232	2045.457	2046.841
2	2049.359	2049.532	2059.587	2062.155	2063.484
3	2063.15	2064.845	2074.322	2077.132	2078.411
4	2070.905	2077.865	2083.962	2087.261	2088.537
5	2076.364	2085.62	2089.201	2093.483	2094.558
6	2078.934	2089.87	2092.41	2098.663	2098.9
7	2079.016	2092.424	2092.424	2101.051	2101.051

Likelihood Ratio

a) model 4 better than model 5

COINT. VECTORS	LR	PROBABILITY
4	2.552	0.465967

b) model 3 better than model 4

COINT. VECTORS	LR	PROBABILITY
4	6.598	0.085877

a) model 2 better than model 3

COINT. VECTORS	LR	PROBABILITY
4	12.194	0.006747

Furthermore, for the group of the seven new countries and the three countries of the EMU case 2: H^*, was chosen. This case allows for linear trend in data (intercept and trend in CE and no trend in VAR).

Table 5

Choise of the appropriate model for the cointegration test

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or	No Intercept	Intercept	Intercept	Intercept	Intercept
No. of CEs	No Trend	No Trend	No Trend	Trend	Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	5	6	5	4	5
Max-Eig	4	2	2	2	2
0	3171.309	3171.309	3188.127	3188.127	3191.565
1	3209.529	3211.065	3227.155	3230.893	3234.267
2	3238.741	3245.923	3261.337	3265.077	3268.244
3	3264.042	3271.411	3286.539	3290.949	3294.103
4	3284.923	3293.546	3305.929	3316.012	3319.05
5	3302.958	3312.907	3322.962	3333.127	3335.818
6	3316.173	3329.593	3335.705	3348.734	3350.765
7	3323.77	3342.19	3348.011	3361.119	3363.141
8	3328.212	3349.203	3353.04	3367.52	3369.181
9	3329.576	3353.586	3354.432	3371.846	3372.178
10	3329.754	3354.621	3354.621	3373.02	3373.02

Likelihood Ratio

a) model 4 better than model 5		
COINT. VECTORS	LR	PROBABILITY
6	4.062	0.397680
b) model 3 better than model 4		
COINT. VECTORS	LR	PROBABILITY
6	26.058	3.08 E-05

As a next step, we construct a VEC Model and from its equation we make a hypothesis testing as far as the variables A(i,1) are concerned. The null hypothesis is H_0: A(i,1)=0 and its purpose is to test whether the country concerned is exogenous or not. An explanation for this is to test which of the countries move towards the restoration of equilibrium when the latter is affected and which are not. From the above test we conduct the following results for the 7 new EU countries:

Table 6

Restrictions on A(i,1) for the 7 new EU countries

COUNTRIES	CHI-SQUARE	PROBABILITY	STATUS
CYPRUS	0,255588	0,613168	Exogenous
CZECH REPUBLIC	16.37260	0.000052	Endogenous
HUNGARY	0.637934	0.424460	Exogenous
LATVIA	4.801170	0.028440	Endogenous
POLAND	0.185298	0.666859	Exogenous
SLOVAK REPUBLIC	1.556603	0.212163	Exogenous
SLOVENIA	1.098100	0.294683	Exogenous

For the group of the 7 new countries, we notice from the cointegration test that the trace test indicates 2 cointegrating equations at the 5% level and 1 cointegrating equation at the 1% level. Furtheremore, the max-eigenvalue test indicates 1 cointegrating equation at the 5% level and no cointegrating equation at the 1% level. From the above hypothesis test for the A(i,1), where the null hypothesis is H_0: A(i,1)=0, we conclude that Cyprus, Hungary, Poland, Slovak Republic and Slovenia do not adjust towards the restoration of equilibrium when the latter is affected. On the contrary, only Czech Republic and Latvia do so.

For the group of the 7 new and the 3 EMU countries, for the same test the results are the following:

Table 7

Restrictions on A(i,1) for the 7 new and the 3 EMU countries

COUNTRIES	CHI-SQUARE	PROBABILITY	STATUS
CYPRUS	1.300314	0.254156	Exogenous
CZECH REPUBLIC	0.548479	0.458940	Exogenous
FRANCE	1.679742	0.194959	Exogenous
GERMANY	17.12727	0.000035	Endogenous
HUNGARY	1.367080	0.242314	Exogenous
LATVIA	3.222882	0.072616	Exogenous
NETHERLANDS	1.300314	0.254156	Exogenous
POLAND	1.447612	0.228912	Exogenous
SLOVAK REPUBLIC	0.046627	0.829040	Exogenous
SLOVENIA	0.648339	0.420707	Exogenous

For the group of the 7 new and the 3 EMU countries, from the above hypothesis test for the A(i,1), where the null hypothesis is H_0: A(i,1)=0, we conclude that Cyprus, Czech Republic, France, Hungary, Latvia, Netherlands, Poland, Slovak Republic and Slovenia do not adjust towards the restoration of equilibrium when the latter is affected. On the contrary, only Germany does so.

As a next step, we conduct a Granger Causality test for the Γ_i that traces out the short-run impact of shocks to the system. The Granger (1969) approach to the question of whether *x* (the industrial production of a country) causes *y* (the industrial production of another country) is to see how much of the current *y* can be explained by past values of *y* and then to see whether adding lagged values of *x* can improve the explanation. *y* is said to be Granger-caused by *x* if *x* helps in the prediction of *y*, or equivalently if the coefficients on the lagged *x*'s are statisticaly significant. Note that two-way causation is frequently the case; *x* Granger causes *y* and *y* Granger causes *x*. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term. A pairwise Granger Causality test tests whether an endogenous variable can be treated as exogenous. For each equation in the VAR, the output displays (Wald) statistics for the joint significance of each of the other lagged endogenous variables in that equation.

In the test described above the null hypothesis is H_0: country *a* does not granger-cause country *b*. The results of this test for the 7 new EU countries are the following:

Table 8

Perwise Granger Causality test for the 7 new EU countries

COUNTRY	RESULT	COUNTRY	PROBABILITY
CYPRUS	Does not Granger cause	CZECH REPUBLIC	0.9258
CYPRUS	Does not Granger cause	HUNGARY	0.0584
CYPRUS	Does not Granger cause	LATVIA	0.3026
CYPRUS	Does not Granger cause	POLAND	0.2959
CYPRUS	Does not Granger cause	SLOVAK REPUBLIC	0.7842
CYPRUS	Does not Granger cause	SLOVENIA	0.4143
CZECH REPUBLIC	Does not Granger cause	CYPRUS	0.1845
CZECH REPUBLIC	Does not Granger cause	HUNGARY	0.5080
CZECH REPUBLIC	Does not Granger cause	LATVIA	0.9434
CZECH REPUBLIC	Does not Granger cause	POLAND	0.8621
CZECH REPUBLIC	Does not Granger cause	SLOVAK REPUBLIC	0.0967
CZECH REPUBLIC	*Does Granger cause*	*SLOVENIA*	*0.0000*
HUNGARY	Does not Granger cause	CYPRUS	0.6722
HUNGARY	Does not Granger cause	CZECH REPUBLIC	0.3602
HUNGARY	Does not Granger cause	LATVIA	0.7048
HUNGARY	Does not Granger cause	POLAND	0.1494
HUNGARY	Does not Granger cause	SLOVAK REPUBLIC	0.2307
HUNGARY	Does not Granger cause	SLOVENIA	0.1052
LATVIA	Does not Granger cause	CYPRUS	0.6146
LATVIA	*Does Granger cause*	*CZECH REPUBLIC*	*0.0105*
LATVIA	Does not Granger cause	HUNGARY	0.6825
LATVIA	Does not Granger cause	POLAND	0.9785
LATVIA	Does not Granger cause	SLOVAK REPUBLIC	0.1983
LATVIA	Does not Granger cause	SLOVENIA	0.8897

COUNTRY	RESULT	COUNTRY	PROBABILITY
POLAND	Does not Granger cause	CYPRUS	0.7959
POLAND	Does not Granger cause	CZECH REPUBLIC	0.5937
POLAND	Does not Granger cause	HUNGARY	0.1984
POLAND	Does not Granger cause	LATVIA	0.6059
POLAND	Does not Granger cause	SLOVAK REPUBLIC	0.3829
POLAND	Does not Granger cause	SLOVENIA	0.0530
SLOVAK REPUBLIC	Does not Granger cause	CYPRUS	0.7109
SLOVAK REPUBLIC	Does not Granger cause	CZECH REPUBLIC	0.8759
SLOVAK REPUBLIC	Does not Granger cause	HUNGARY	0.2281
SLOVAK REPUBLIC	Does not Granger cause	LATVIA	0.2566
SLOVAK REPUBLIC	Does not Granger cause	POLAND	0.0878
SLOVAK REPUBLIC	Does not Granger cause	SLOVENIA	0.3993
SLOVENIA	Does not Granger cause	CYPRUS	0.4352
SLOVENIA	*Does Granger cause*	*CZECH REPUBLIC*	*0.0084*
SLOVENIA	Does not Granger cause	HUNGARY	0.4334
SLOVENIA	Does not Granger cause	LATVIA	0.5157
SLOVENIA	Does not Granger cause	POLAND	0.1843
SLOVENIA	Does not Granger cause	SLOVAK REPUBLIC	0.7808

From the above results, we conclude that we have a two-way causation between Slovenia and Czech Republic and that Latvia does Granger cause to Czech Republic. As we can see, an alteration in the series of the industrial production of Cyprus is not affected by the history of the dynamics of Czech Republic, Hungary, Latvia, Poland, Slovak Republic and Slovenia. Czech Republic's series is not affected by the history of Cyprus, Hungary, Latvia, Poland and Slovak Republic. Hungary's series is not affected by the history of Cyprus, Czech Republic, Latvia, Poland, Slovak Republic and Slovenia. Latvia's series is not affected by the history of Cyprus, Hungary, Latvia, Poland, Slovak Republic and Slovenia. Poland's series is not affected by the history of Cyprus, Czech Republic, Hungary, Latvia, Slovak Republic and Slovenia. Slovak Republic's series is not affected by the history of Cyprus, Czech Republic, Hungary, Latvia, Poland and Slovenia. Finally, Slovenia's series is not affected by the history of Cyprus, Hungary, Latvia, Poland, Slovak Republic and Slovenia.

The results of this test for the 7 new and the 3 EMU countries are the following:

Table 9

Perwise Granger Causality test for the 7 new and the 3 EMU countries

COUNTRY	RESULT	COUNTRY	PROBABILITY
CYPRUS	Does not Granger cause	CZECH REPUBLIC	0.4978
CYPRUS	*Does Granger cause*	*FRANCE*	*0.0015*
CYPRUS	Does not Granger cause	GERMANY	0.6709
CYPRUS	Does not Granger cause	HUNGARY	0.0766
CYPRUS	Does not Granger cause	LATVIA	0.2408
CYPRUS	Does not Granger cause	NETHERLANDS	0.6224
CYPRUS	Does not Granger cause	POLAND	0.2947
CYPRUS	Does not Granger cause	SLOVAK REPUBLIC	0.9463
CYPRUS	Does not Granger cause	SLOVENIA	0.1320
CZECH REPUBLIC	Does not Granger cause	CYPRUS	0.3051
CZECH REPUBLIC	Does not Granger cause	FRANCE	0.3161
CZECH REPUBLIC	Does not Granger cause	GERMANY	0.1150
CZECH REPUBLIC	Does not Granger cause	HUNGARY	0.2061
CZECH REPUBLIC	Does not Granger cause	LATVIA	0.0747
CZECH REPUBLIC	*Does Granger cause*	*NETHERLANDS*	*0.0454*
CZECH REPUBLIC	Does not Granger cause	POLAND	0.5259
CZECH REPUBLIC	*Does Granger cause*	*SLOVAK REPUBLIC*	*0.0059*
CZECH REPUBLIC	*Does Granger cause*	*SLOVENIA*	*0.0015*
FRANCE	Does not Granger cause	CYPRUS	0.4019
FRANCE	Does not Granger cause	CZECH REPUBLIC	0.7057
FRANCE	Does not Granger cause	GERMANY	0.3000
FRANCE	Does not Granger cause	HUNGARY	0.1662
FRANCE	Does not Granger cause	LATVIA	0.9327
FRANCE	Does not Granger cause	NETHERLANDS	0.6535

FRANCE	Does not Granger cause	POLAND	0.7072
FRANCE	Does not Granger cause	SLOVAK REPUBLIC	0.5923
FRANCE	Does not Granger cause	SLOVENIA	0.2210
GERMANY	*Does Granger cause*	*CYPRUS*	*0.0002*
GERMANY	*Does Granger cause*	*CZECH REPUBLIC*	*0.0069*
GERMANY	Does not Granger cause	FRANCE	0.7893
GERMANY	Does not Granger cause	HUNGARY	0.2396
GERMANY	Does not Granger cause	LATVIA	0.0546
GERMANY	*Does Granger cause*	*NETHERLANDS*	*0.0001*
GERMANY	*Does Granger cause*	*POLAND*	*0.0078*
GERMANY	Does not Granger cause	SLOVAK REPUBLIC	0.2151
GERMANY	Does not Granger cause	SLOVENIA	0.1566
HUNGARY	Does not Granger cause	CYPRUS	0.4476
HUNGARY	Does not Granger cause	CZECH REPUBLIC	0.2212
HUNGARY	Does not Granger cause	FRANCE	0.3421
HUNGARY	Does not Granger cause	GERMANY	0.0693
HUNGARY	Does not Granger cause	LATVIA	0.7173
HUNGARY	Does not Granger cause	NETHERLANDS	0.1734
HUNGARY	Does not Granger cause	POLAND	0.0749
HUNGARY	Does not Granger cause	SLOVAK REPUBLIC	0.2327
HUNGARY	Does not Granger cause	SLOVENIA	0.1377
LATVIA	Does not Granger cause	CYPRUS	0.4832
LATVIA	*Does Granger cause*	*CZECH REPUBLIC*	*0.0154*
LATVIA	Does not Granger cause	FRANCE	0.2863
LATVIA	Does not Granger cause	GERMANY	0.8361
LATVIA	Does not Granger cause	HUNGARY	0.4076
LATVIA	Does not Granger cause	NETHERLANDS	0.3893
LATVIA	Does not Granger cause	POLAND	0.9959
LATVIA	*Does Granger cause*	*SLOVAK REPUBLIC*	*0.0422*
LATVIA	Does not Granger cause	SLOVENIA	0.5433
NETHERLANDS	Does not Granger cause	CYPRUS	0.5969
NETHERLANDS	Does not Granger cause	CZECH REPUBLIC	0.6303
NETHERLANDS	Does not Granger cause	FRANCE	0.6541

NETHERLANDS	Does not Granger cause	GERMANY	0.8827
NETHERLANDS	Does not Granger cause	HUNGARY	0.3005
NETHERLANDS	Does not Granger cause	LATVIA	0.4724
NETHERLANDS	Does not Granger cause	POLAND	0.1139
NETHERLANDS	Does not Granger cause	SLOVAK REPUBLIC	0.3919
NETHERLANDS	Does not Granger cause	SLOVENIA	0.6573
POLAND	Does not Granger cause	CYPRUS	0,8408
POLAND	Does not Granger cause	CZECH REPUBLIC	0,7675
POLAND	Does not Granger cause	FRANCE	0,5372
POLAND	Does not Granger cause	GERMANY	0,5723
POLAND	Does not Granger cause	HUNGARY	0,0962
POLAND	Does not Granger cause	LATVIA	0,7310
POLAND	Does not Granger cause	NETHERLANDS	0,1251
POLAND	Does not Granger cause	SLOVAK REPUBLIC	0,5018
POLAND	*Does Granger cause*	*SLOVENIA*	*0,0483*
SLOVAK REPUBLIC	Does not Granger cause	CYPRUS	0,8869
SLOVAK REPUBLIC	Does not Granger cause	CZECH REPUBLIC	0,9848
SLOVAK REPUBLIC	Does not Granger cause	FRANCE	0,1327
SLOVAK REPUBLIC	Does not Granger cause	GERMANY	0,1536
SLOVAK REPUBLIC	Does not Granger cause	HUNGARY	0,2667
SLOVAK REPUBLIC	*Does Granger cause*	*LATVIA*	*0,0386*
SLOVAK REPUBLIC	Does not Granger cause	NETHERLANDS	0,2162
SLOVAK REPUBLIC	*Does Granger cause*	*POLAND*	*0,0329*
SLOVAK REPUBLIC	Does not Granger cause	SLOVENIA	0,7998
SLOVENIA	Does not Granger cause	CYPRUS	0,2849
SLOVENIA	*Does Granger cause*	*CZECH REPUBLIC*	*0,0085*
SLOVENIA	Does not Granger cause	FRANCE	0,9001
SLOVENIA	*Does Granger cause*	*GERMANY*	*0,0200*
SLOVENIA	Does not Granger cause	HUNGARY	0,2373
SLOVENIA	Does not Granger cause	LATVIA	0,1732
SLOVENIA	Does not Granger cause	NETHERLANDS	0,7925
SLOVENIA	Does not Granger cause	POLAND	0,0532
SLOVENIA	Does not Granger cause	SLOVAK REPUBLIC	0,6576

From the above results as we can see, an alteration in the series of industrial production of Cyprus is not affected by the history of all the other countries except France. Czech's series is not affected by the history of all the other countries except Netherlands, Slovak Republic and Slovenia. Germany's series is not affected by the history of all the other countries except Cyprus, Czech, Netherlands and Poland. Hungary's series is not affected by the history of all the other countries. Latvia's series is not affected by the history of all the other countries except Czech and Slovak Republic. Netherlands' series is not affected by the history of all the other countries. Poland's series is not affected by the history of all the other countries except Slovenia. Slovakia's series is not affected by the history of all the other countries except Latvia and Poland. Slovenia's series is not affected by the history of all the other countries except Czech and Germany.

Finally, we proceed in testing whether the cointegrating coefficients B(1,i) participate in the cointegrating equation. This is achieved through a hypothesis testing with null hypothesis H_0: B(1,i)=0. From the above test we conduct the following results for the 7 new EU countries:

Table 10

Restrictions on B(1,i) for the 7 new EU countries

COUNTRY	CHI-SQUARE	PROBABILITY	RESULT
CYPRUS	0.555195	0.456203	Doesn't participate
CZECH REPUBLIC	10,04098	0.001531	Participates
HUNGARY	0.553083	0.457061	Doesn't participate
LATVIA	13.73000	0.000211	Participates
POLAND	0.005968	0.938424	Doesn't participate
SLOVAK REPUBLIC	0.495098	0.481662	Doesn't participate
SLOVENIA	0.097684	0.754627	Doesn't participate

From the above results, we conclude that only Czech Republic and Latvia participate in the cointegrating equation.

For the 7 new and the 3 EMU countries we conduct the following results:

Table 11

Restrictions on B(1,i) for the 7 new and the 3 EMU countries

COUNTRY	CHI-SQUARE	PROBABILITY	RESULT
CYPRUS	7.527113	0.006078	Participate
CZECH REPUBLIC	3.400234	0.065187	Doesn't participate
FRANCE	1.538785	0.214799	Doesn't participate
GERMANY	15.09762	0.000102	Participate
HUNGARY	6.283079	0.012190	Participate
LATVIA	4.405046	0.035833	Participate
NETHERLANDS	3.093923	0.078585	Doesn't participate
POLAND	0.609497	0.434977	Doesn't participate
SLOVAK REPUBLIC	0.344931	0.556997	Doesn't participate
SLOVENIA	0.010014	0.920289	Doesn't participate

From the above results, we conclude that only Cyprus, Germany, Hungary and Latvia participate in the cointegrating equation.

At last, from the cointegration test for the 7 new EU countries trace test indicates two cointegrating vectors at the 5% level and therefore 5 common trends.

For the 7 new and the 3 EMU countries trace indicates 4 cointegrating vectors at both 5% and 1% levels and therefore 6 common trends.

6. CONCLUSIONS

In this paper we have presented cointegration analysis among the 10 new EU countries alone, as well as in relation to 3 EMU countries. Cointegration is a necessary condition for co-movement of key variables in the long run and, thus for a successful future accession of the new countries into the EMU. The analysis was based on an aspect of real convergence, using as a proxy the industrial production series of those countries. We attempt to answer the question of whether there is convergence in output (industrial production) in these countries. We first appose a stochastic definition of convergence based on the theory of integrated time series.

For the interpretation of the empirical results, we claim that there is "complete" convergence of government policies in a group of p countries, if we find that there exist $r = p - 1$ cointegrating vectors and a single shared common stochastic trend in a set of variables such as industrial production. On the other hand, if $0 < r < p - 1$, then there is only "partial" convergence among the policies of the countries concerned. In this sense, convergence means that the countries' policies are aligned enough, so that the relevant variables move towards a long run equilibrium and do not drift too far apart over time. Time series of industrial production of different countries can fail to converge only if the persistent parts of the time series are dinstinct.

In the case of industrial production our analysis indicates no convergence among the 7 new countries, as 2 cointegrating vectors aren't sufficient to conclude partial convergence, and only partial convergence among the 7 new and the 3 EMU countries.

In the long run, as far as the 7 new countries are concerned, Cyprus, Hungary, Poland, Slovak Republic and Slovenia do not adjust towards the restoration of equilibrium when the latter is affected. On the contrary, only

Czech Republic and Latvia do so. Furthermore, we conclude that only Czech Republic and Latvia participate in the cointegrating equation.

In the group of the 7 new and the 3 EMU countries Cyprus, Czech Republic, France, Hungary, Latvia, Netherlands, Poland, Slovak Republic and Slovenia do not adjust towards the restoration of equilibrium when the latter is affected. On the contrary, only Germany does so. Furthermore, Cyprus, Germany, Hungary and Latvia participate in the cointegrating equation.

As there exist five common stochastic trends among the industrial production series of the 7 new EU countries, then these countries set their policies independently in the long run. In the group of the 7 new and 3 EMU countries there exist six common stochastic trends, consequently, there is only partial convergence of policies and some further adjustment in the policies of some countries may be required to successfully reach a long run equilibrium.

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APPENDIX

Cointegration among the 7 new EU countries

Cointegration Test (Model 6)

Date: 06/23/04 Time: 23:11
Sample: 1993:01 2003:12
Included observations: 128
Series: CYP_LOG CZ_LOG HUN_LOG LAT_LOG POL_LOG SLVK_LOG SLVN_LOG
Lags interval: 1 to 1

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	2	4	2	1	2
Max-Eig	2	1	1	1	1
Log Likelihood by Rank (rows) and Model (columns)					
0	2005.124	2005.124	2020.350	2020.350	2022.404
1	2030.865	2031.004	2044.232	2045.457	2046.841
2	2049.359	2049.532	2059.587	2062.155	2063.484
3	2063.150	2064.845	2074.322	2077.132	2078.411
4	2070.905	2077.865	2083.962	2087.261	2088.537
5	2076.364	2085.620	2089.201	2093.483	2094.558
6	2078.934	2089.870	2092.410	2098.663	2098.900
7	2079.016	2092.424	2092.424	2101.051	2101.051
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	-30.56444	-30.56444	-30.69297	-30.69297	-30.61569
1	-30.74789	-30.73444	-30.84738	-30.85090	-30.77876
2	-30.81810	-30.78956	-30.86855	-30.87742	-30.82006
3	-30.81484	-30.79445	-30.88003*	-30.87707	-30.83454
4	-30.71727	-30.76351	-30.81191	-30.80095	-30.77402
5	-30.58381	-30.65031	-30.67502	-30.66379	-30.64934
6	-30.40521	-30.48234	-30.50640	-30.51036	-30.49844
7	-30.18775	-30.28787	-30.28787	-30.31330	-30.31330
Schwarz Criteria by Rank (rows) and Model (columns)					
0	-29.47265*	-29.47265*	-29.44520	-29.44520	-29.21195
1	-29.34415	-29.30842	-29.28767	-29.26891	-29.06309
2	-29.10243	-29.02933	-28.99690	-28.96121	-28.79245
3	-28.78723	-28.69999	-28.69644	-28.62664	-28.49498
4	-28.37771	-28.33483	-28.31639	-28.21630	-28.12252
5	-27.93232	-27.88741	-27.86755	-27.74491	-27.68590
6	-27.44178	-27.38521	-27.38699	-27.25727	-27.22307
7	-26.91237	-26.85652	-26.85652	-26.72598	-26.72598

ESTIMATION
VEC Model - (Model 3, lags 1)

Vector Error Correction Estimates
Date: 06/23/04 Time: 23:46
Sample(adjusted): 1993:03 2003:10
Included observations: 128 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
CYP_LOG(-1)	1.000000
CZ_LOG(-1)	2.321086 (0.48752) [4.76102]
HUN_LOG(-1)	-0.286174 (0.28431) [-1.00656]
LAT_LOG(-1)	-1.194195 (0.19535) [-6.11322]
POL_LOG(-1)	-0.025112 (0.26550) [-0.09459]
SLVK_LOG(-1)	-0.700512 (0.62481) [-1.12115]
SLVN_LOG(-1)	-0.525462 (0.99856) [-0.52622]
C	-2.726570

Error Correction:	D(CYP_LOG)	D(CZ_LOG)	D(HUN_LOG)	D(LAT_LOG)	D(POL_LOG)	D(SLVK_LOG)	D(SLVN_LOG)
CointEq1	-0.013614 (0.01881) [-0.72385]	-0.124936 (0.02136) [-5.84845]	0.012023 (0.01500) [0.80130]	0.108414 (0.04571) [2.37171]	-0.015240 (0.03345) [-0.45553]	-0.029282 (0.01840) [-1.59165]	-0.009489 (0.00659) [-1.44042]
D(CYP_LOG(-1))	-0.579214 (0.07319) [-7.91351]	0.110310 (0.08313) [1.32692]	-0.024707 (0.05839) [-0.42313]	-0.089558 (0.17789) [-0.50345]	-0.033667 (0.13019) [-0.25860]	-0.026537 (0.07159) [-0.37066]	0.020005 (0.02564) [0.78036]
D(CZ_LOG(-1))	0.005129 (0.05505) [0.09317]	-0.424715 (0.06253) [-6.79206]	-0.040184 (0.04392) [-0.91490]	-0.342505 (0.13381) [-2.55973]	-0.052241 (0.09793) [-0.53347]	-0.008407 (0.05385) [-0.15611]	0.050795 (0.01928) [2.63425]
D(HUN_LOG(-1))	-0.200191 (0.10577) [-1.89263]	-0.079532 (0.12014) [-0.66201]	-0.368229 (0.08438) [-4.36370]	0.105151 (0.25707) [0.40903]	-0.241954 (0.18814) [-1.28602]	-0.124711 (0.10346) [-1.20537]	-0.029024 (0.03705) [-0.78343]
D(LAT_LOG(-1))	-0.036864 (0.03576) [-1.03090]	0.002881 (0.04062) [0.07094]	-0.010807 (0.02853) [-0.37881]	-0.281631 (0.08691) [-3.24050]	0.032817 (0.06361) [0.51595]	0.039681 (0.03498) [1.13445]	0.008140 (0.01252) [0.64995]
D(POL_LOG(-1))	0.057845 (0.05534) [1.04529]	0.010915 (0.06285) [0.17366]	0.063650 (0.04415) [1.44174]	-0.003619 (0.13450) [-0.02691]	-0.256946 (0.09843) [-2.61040]	-0.092420 (0.05413) [-1.70737]	-0.025730 (0.01938) [-1.32751]
D(SLVK_LOG(-1))	-0.026940 (0.09835) [-0.27391]	0.185543 (0.11171) [1.66092]	-0.094037 (0.07847) [-1.19846]	-0.307528 (0.23904) [-1.28651]	-0.152662 (0.17494) [-0.87263]	-0.318564 (0.09621) [-3.31127]	0.009586 (0.03445) [0.27828]
D(SLVN_LOG(-1))	0.212359 (0.26016) [0.81626]	-1.386517 (0.29549) [-4.69231]	0.336260 (0.20755) [1.62015]	0.087700 (0.63229) [0.13870]	-0.895427 (0.46275) [-1.93503]	-0.214490 (0.25448) [-0.84287]	0.145849 (0.09112) [1.60065]
C	0.002331 (0.00241) [0.96550]	0.006914 (0.00274) [2.52102]	0.008855 (0.00193) [4.59657]	0.008532 (0.00587) [1.45375]	0.008025 (0.00430) [1.86839]	0.006429 (0.00236) [2.72163]	0.001773 (0.00085) [2.09664]
R-squared	0.391870	0.539822	0.178869	0.228987	0.166436	0.218732	0.115686
Adj. R-squared	0.350988	0.508885	0.123667	0.177154	0.110398	0.166210	0.056236
Sum sq. resids	0.076770	0.099036	0.048861	0.453466	0.242885	0.073452	0.009417
S.E. equation	0.025399	0.028848	0.020263	0.061730	0.045178	0.024844	0.008896
F-statistic	9.585249	17.44942	3.240260	4.417789	2.970059	4.164559	1.945946
Log likelihood	293.1900	276.8913	322.1081	179.5192	219.4764	296.0173	427.4784
Akaike AIC	-4.440469	-4.185802	-4.892314	-2.664362	-3.288694	-4.484646	-6.538724
Schwarz SC	-4.239936	-3.985268	-4.691780	-2.463829	-3.088161	-4.284112	-6.338191
Mean dependent	0.000813	0.002759	0.006559	0.005363	0.003127	0.003823	0.002069
S.D. dependent	0.031528	0.041165	0.021646	0.068052	0.047899	0.027208	0.009157

Determinant Residual Covariance	5.28E-23
Log Likelihood	2044.232
Log Likelihood (d.f. adjusted)	2011.570
Akaike Information Criteria	-30.33703
Schwarz Criteria	-28.77733

VEC Model Equation

```
Estimation Proc:
===============================
EC(C,1) 1 1 CYP_LOG CZ_LOG HUN_LOG LAT_LOG POL_LOG SLVK_LOG SLVN_LOG

VAR Model:
===============================
D(CYP_LOG) = A(1,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*HUN_LOG(-1) + B(1,4)*LAT_LOG(-1) + B(1,5)*POL_LOG(-1) + B(1,6)*SLVK_LOG(-1) +
B(1,7)*SLVN_LOG(-1) + B(1,8)) + C(1,1)*D(CYP_LOG(-1)) + C(1,2)*D(CZ_LOG(-1)) + C(1,3)*D(HUN_LOG(-1)) + C(1,4)*D(LAT_LOG(-1)) + C(1,5)*D(POL_LOG(-1)) +
C(1,6)*D(SLVK_LOG(-1)) + C(1,7)*D(SLVN_LOG(-1)) + C(1,8)

D(CZ_LOG) = A(2,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*HUN_LOG(-1) + B(1,4)*LAT_LOG(-1) + B(1,5)*POL_LOG(-1) + B(1,6)*SLVK_LOG(-1) +
B(1,7)*SLVN_LOG(-1) + B(1,8)) + C(2,1)*D(CYP_LOG(-1)) + C(2,2)*D(CZ_LOG(-1)) + C(2,3)*D(HUN_LOG(-1)) + C(2,4)*D(LAT_LOG(-1)) + C(2,5)*D(POL_LOG(-1)) +
C(2,6)*D(SLVK_LOG(-1)) + C(2,7)*D(SLVN_LOG(-1)) + C(2,8)

D(HUN_LOG) = A(3,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*HUN_LOG(-1) + B(1,4)*LAT_LOG(-1) + B(1,5)*POL_LOG(-1) + B(1,6)*SLVK_LOG(-1) +
B(1,7)*SLVN_LOG(-1) + B(1,8)) + C(3,1)*D(CYP_LOG(-1)) + C(3,2)*D(CZ_LOG(-1)) + C(3,3)*D(HUN_LOG(-1)) + C(3,4)*D(LAT_LOG(-1)) + C(3,5)*D(POL_LOG(-1)) +
C(3,6)*D(SLVK_LOG(-1)) + C(3,7)*D(SLVN_LOG(-1)) + C(3,8)

D(LAT_LOG) = A(4,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*HUN_LOG(-1) + B(1,4)*LAT_LOG(-1) + B(1,5)*POL_LOG(-1) + B(1,6)*SLVK_LOG(-1) +
B(1,7)*SLVN_LOG(-1) + B(1,8)) + C(4,1)*D(CYP_LOG(-1)) + C(4,2)*D(CZ_LOG(-1)) + C(4,3)*D(HUN_LOG(-1)) + C(4,4)*D(LAT_LOG(-1)) + C(4,5)*D(POL_LOG(-1)) +
C(4,6)*D(SLVK_LOG(-1)) + C(4,7)*D(SLVN_LOG(-1)) + C(4,8)

D(POL_LOG) = A(5,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*HUN_LOG(-1) + B(1,4)*LAT_LOG(-1) + B(1,5)*POL_LOG(-1) + B(1,6)*SLVK_LOG(-1) +
B(1,7)*SLVN_LOG(-1) + B(1,8)) + C(5,1)*D(CYP_LOG(-1)) + C(5,2)*D(CZ_LOG(-1)) + C(5,3)*D(HUN_LOG(-1)) + C(5,4)*D(LAT_LOG(-1)) + C(5,5)*D(POL_LOG(-1)) +
C(5,6)*D(SLVK_LOG(-1)) + C(5,7)*D(SLVN_LOG(-1)) + C(5,8)

D(SLVK_LOG) = A(6,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*HUN_LOG(-1) + B(1,4)*LAT_LOG(-1) + B(1,5)*POL_LOG(-1) + B(1,6)*SLVK_LOG(-1) +
B(1,7)*SLVN_LOG(-1) + B(1,8)) + C(6,1)*D(CYP_LOG(-1)) + C(6,2)*D(CZ_LOG(-1)) + C(6,3)*D(HUN_LOG(-1)) + C(6,4)*D(LAT_LOG(-1)) + C(6,5)*D(POL_LOG(-1)) +
C(6,6)*D(SLVK_LOG(-1)) + C(6,7)*D(SLVN_LOG(-1)) + C(6,8)

D(SLVN_LOG) = A(7,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*HUN_LOG(-1) + B(1,4)*LAT_LOG(-1) + B(1,5)*POL_LOG(-1) + B(1,6)*SLVK_LOG(-1) +
B(1,7)*SLVN_LOG(-1) + B(1,8)) + C(7,1)*D(CYP_LOG(-1)) + C(7,2)*D(CZ_LOG(-1)) + C(7,3)*D(HUN_LOG(-1)) + C(7,4)*D(LAT_LOG(-1)) + C(7,5)*D(POL_LOG(-1)) +
C(7,6)*D(SLVK_LOG(-1)) + C(7,7)*D(SLVN_LOG(-1)) + C(7,8)

VAR Model - Substituted Coefficients:
===============================
D(CYP_LOG) =  - 0.01361429947*( CYP_LOG(-1) + 2.321086061*CZ_LOG(-1) - 0.2861742391*HUN_LOG(-1) - 1.194195353*LAT_LOG(-1) - 0.02511231361*POL_LOG(-1) -
0.7005122995*SLVK_LOG(-1) - 0.5254621077*SLVN_LOG(-1) - 2.726570022 ) - 0.5792136578*D(CYP_LOG(-1)) + 0.005129487695*D(CZ_LOG(-1)) -
0.2001910889*D(HUN_LOG(-1)) - 0.03686446625*D(LAT_LOG(-1)) + 0.05784496821*D(POL_LOG(-1)) - 0.02694015717*D(SLVK_LOG(-1)) + 0.2123585534*D(SLVN_LOG(-
1)) + 0.002331495397

D(CZ_LOG) =  - 0.1249355243*( CYP_LOG(-1) + 2.321086061*CZ_LOG(-1) - 0.2861742391*HUN_LOG(-1) - 1.194195353*LAT_LOG(-1) - 0.02511231361*POL_LOG(-1) -
0.7005122995*SLVK_LOG(-1) - 0.5254621077*SLVN_LOG(-1) - 2.726570022 ) + 0.1103096646*D(CYP_LOG(-1)) - 0.4247153171*D(CZ_LOG(-1)) -
0.07953179898*D(HUN_LOG(-1)) + 0.002881465074*D(LAT_LOG(-1)) + 0.01091514685*D(POL_LOG(-1)) + 0.1855432011*D(SLVK_LOG(-1)) -
1.386517009*D(SLVN_LOG(-1)) + 0.006914458925

D(HUN_LOG) = 0.01202335816*( CYP_LOG(-1) + 2.321086061*CZ_LOG(-1) - 0.2861742391*HUN_LOG(-1) - 1.194195353*LAT_LOG(-1) - 0.02511231361*POL_LOG(-1) -
0.7005122995*SLVK_LOG(-1) - 0.5254621077*SLVN_LOG(-1) - 2.726570022 ) - 0.02470714471*D(CYP_LOG(-1)) - 0.0401838243*D(CZ_LOG(-1)) -
0.3682286438*D(HUN_LOG(-1)) - 0.01080673193*D(LAT_LOG(-1)) + 0.0636503532*D(POL_LOG(-1)) - 0.09403729246*D(SLVK_LOG(-1)) + 0.3362604201*D(SLVN_LOG(-
1)) + 0.008855190782

D(LAT_LOG) = 0.1084136008*( CYP_LOG(-1) + 2.321086061*CZ_LOG(-1) - 0.2861742391*HUN_LOG(-1) - 1.194195353*LAT_LOG(-1) - 0.02511231361*POL_LOG(-1) -
0.7005122995*SLVK_LOG(-1) - 0.5254621077*SLVN_LOG(-1) - 2.726570022 ) - 0.08955820252*D(CYP_LOG(-1)) - 0.3425053969*D(CZ_LOG(-1)) +
0.105150634*D(HUN_LOG(-1)) - 0.2816309094*D(LAT_LOG(-1)) - 0.003618716708*D(POL_LOG(-1)) - 0.3075278045*D(SLVK_LOG(-1)) + 0.0876999262*D(SLVN_LOG(-1))
+ 0.008531943931

D(POL_LOG) =  - 0.01523950179*( CYP_LOG(-1) + 2.321086061*CZ_LOG(-1) - 0.2861742391*HUN_LOG(-1) - 1.194195353*LAT_LOG(-1) - 0.02511231361*POL_LOG(-1) -
0.7005122995*SLVK_LOG(-1) - 0.5254621077*SLVN_LOG(-1) - 2.726570022 ) - 0.03366708733*D(CYP_LOG(-1)) - 0.05224103104*D(CZ_LOG(-1)) -
0.2419541071*D(HUN_LOG(-1)) + 0.03281718483*D(LAT_LOG(-1)) - 0.2569459732*D(POL_LOG(-1)) - 0.1526615015*D(SLVK_LOG(-1)) - 0.8954268331*D(SLVN_LOG(-1))
+ 0.008025143753

D(SLVK_LOG) =  - 0.0292818619*( CYP_LOG(-1) + 2.321086061*CZ_LOG(-1) - 0.2861742391*HUN_LOG(-1) - 1.194195353*LAT_LOG(-1) - 0.02511231361*POL_LOG(-1) -
0.7005122995*SLVK_LOG(-1) - 0.5254621077*SLVN_LOG(-1) - 2.726570022 ) - 0.02653695115*D(CYP_LOG(-1)) - 0.008406744688*D(CZ_LOG(-1)) -
0.1247110819*D(HUN_LOG(-1)) + 0.03968116019*D(LAT_LOG(-1)) - 0.09242004049*D(POL_LOG(-1)) - 0.3185644933*D(SLVK_LOG(-1)) - 0.2144901123*D(SLVN_LOG(-
1)) + 0.006428613025

D(SLVN_LOG) =  - 0.009488609926*( CYP_LOG(-1) + 2.321086061*CZ_LOG(-1) - 0.2861742391*HUN_LOG(-1) - 1.194195353*LAT_LOG(-1) - 0.02511231361*POL_LOG(-
1) - 0.7005122995*SLVK_LOG(-1) - 0.5254621077*SLVN_LOG(-1) - 2.726570022 ) + 0.02000488766*D(CYP_LOG(-1)) + 0.05079514822*D(CZ_LOG(-1)) -
0.02902358531*D(HUN_LOG(-1)) + 0.008140284843*D(LAT_LOG(-1)) - 0.02572984529*D(POL_LOG(-1)) + 0.009586110021*D(SLVK_LOG(-1)) +
0.1458494183*D(SLVN_LOG(-1)) + 0.001773266423
```

Cointegration Test

Date: 06/24/04 Time: 00:36
Sample(adjusted): 1993:03 2003:10
Included observations: 128 after adjusting endpoints
Trend assumption: Linear deterministic trend
Series: CYP_LOG CZ_LOG HUN_LOG LAT_LOG POL_LOG SLVK_LOG SLVN_LOG
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.311444	144.1478	124.24	133.57
At most 1 *	0.213311	96.38340	94.15	103.18
At most 2	0.205649	65.67335	68.52	76.07
At most 3	0.139838	36.20392	47.21	54.46
At most 4	0.078597	16.92264	29.68	35.65
At most 5	0.048895	6.444840	15.41	20.04
At most 6	0.000219	0.028080	3.76	6.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Trace test indicates 2 cointegrating equation(s) at the 5% level
Trace test indicates 1 cointegrating equation(s) at the 1% level

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 Percent Critical Value	1 Percent Critical Value
None *	0.311444	47.76436	45.28	51.57
At most 1	0.213311	30.71005	39.37	45.10
At most 2	0.205649	29.46943	33.46	38.77
At most 3	0.139838	19.28128	27.07	32.24
At most 4	0.078597	10.47780	20.97	25.52
At most 5	0.048895	6.416761	14.07	18.63
At most 6	0.000219	0.028080	3.76	6.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Max-eigenvalue test indicates 1 cointegrating equation(s) at the 5% level
Max-eigenvalue test indicates no cointegration at the 1% level

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

CYP_LOG	CZ_LOG	HUN_LOG	LAT_LOG	POL_LOG	SLVK_LOG	SLVN_LOG
-8.377758	-19.44550	2.397499	10.00468	0.210385	5.868722	4.402194
-6.568741	-9.380477	4.754130	4.225706	2.887595	22.84917	-52.14268
44.86974	-10.07921	-8.640808	2.742841	-0.392084	23.21919	-18.30798
-22.62622	-15.72665	-0.072105	-2.047556	-11.05183	16.74715	22.01805
-3.470202	-6.110114	-10.69807	-2.556655	9.924453	3.777564	25.58312
-9.110243	6.455740	-10.87250	0.469120	5.946981	10.77799	6.074615
-1.069761	-2.652223	1.816799	-3.052663	2.653852	3.563887	3.281841

Unrestricted Adjustment Coefficients (alpha):

D(CYP_LOG)	0.001625	0.001457	-0.010136	0.001971	0.001881	0.000677	2.22E-05
D(CZ_LOG)	0.014913	0.001167	0.002711	0.002002	0.003278	-0.001761	-4.93E-05
D(HUN_LOG)	-0.001435	5.83E-05	0.000202	-0.001802	0.002293	0.000564	-0.000248
D(LAT_LOG)	-0.012941	0.005071	0.002124	0.000644	0.007687	-0.010530	-4.09E-05
D(POL_LOG)	0.001819	0.003148	-0.001448	0.006135	-0.006242	-0.003592	-0.000420
D(SLVK_LOG)	0.003495	-0.005462	-0.004090	-0.002721	-0.002527	-0.002810	-8.11E-05
D(SLVN_LOG)	0.001133	0.002733	-0.000837	-0.001745	-0.000162	-0.000698	-7.12E-06

1 Cointegrating Equation(s): Log likelihood 2044.232

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	HUN_LOG	LAT_LOG	POL_LOG	SLVK_LOG	SLVN_LOG
1.000000	2.321086	-0.286174	-1.194195	-0.025112	-0.700512	-0.525462
	(0.48752)	(0.28431)	(0.19535)	(0.26550)	(0.62481)	(0.99856)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.013614
	(0.01881)
D(CZ_LOG)	-0.124936
	(0.02136)
D(HUN_LOG)	0.012023
	(0.01500)
D(LAT_LOG)	0.108414
	(0.04571)
D(POL_LOG)	-0.015240
	(0.03345)

D(SLVK_LOG)	-0.029282
	(0.01840)
D(SLVN_LOG)	-0.009489
	(0.00659)

2 Cointegrating Equation(s): Log likelihood 2059.587

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	HUN_LOG	LAT_LOG	POL_LOG	SLVK_LOG	SLVN_LOG
1.000000	0.000000	-1.423474	0.237617	-1.102394	-7.920676	21.47184
		(1.29936)	(0.73347)	(1.18043)	(2.05093)	(4.54728)
0.000000	1.000000	0.489986	-0.616872	0.464128	3.110683	-9.477160
		(0.61349)	(0.34631)	(0.55734)	(0.96834)	(2.14699)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.023187	-0.045270
	(0.02386)	(0.04838)
D(CZ_LOG)	-0.132601	-0.300932
	(0.02712)	(0.05500)
D(HUN_LOG)	0.011641	0.027361
	(0.01907)	(0.03867)
D(LAT_LOG)	0.075106	0.204072
	(0.05788)	(0.11737)
D(POL_LOG)	-0.035916	-0.064900
	(0.04240)	(0.08599)
D(SLVK_LOG)	0.006595	-0.016732
	(0.02276)	(0.04616)
D(SLVN_LOG)	-0.027444	-0.047665
	(0.00793)	(0.01609)

3 Cointegrating Equation(s): Log likelihood 2074.322

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	HUN_LOG	LAT_LOG	POL_LOG	SLVK_LOG	SLVN_LOG
1.000000	0.000000	0.000000	-0.096826	0.169227	1.778428	-4.014142
			(0.12953)	(0.18879)	(0.34302)	(0.71537)
0.000000	1.000000	0.000000	-0.501750	0.026413	-0.227927	-0.704413
			(0.07302)	(0.10643)	(0.19338)	(0.40331)
0.000000	0.000000	1.000000	-0.234948	0.893321	6.813683	-17.90407
			(0.58475)	(0.85230)	(1.54857)	(3.22961)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.477975	0.056890	0.098405
	(0.09404)	(0.04859)	(0.02070)
D(CZ_LOG)	-0.010954	-0.328258	0.017875
	(0.11692)	(0.06041)	(0.02573)
D(HUN_LOG)	0.020682	0.025330	-0.004905
	(0.08259)	(0.04267)	(0.01818)
D(LAT_LOG)	0.170413	0.182663	-0.025273
	(0.25054)	(0.12945)	(0.05514)
D(POL_LOG)	-0.100882	-0.050306	0.031837
	(0.18357)	(0.09484)	(0.04040)
D(SLVK_LOG)	-0.176903	0.024488	0.017751
	(0.09707)	(0.05016)	(0.02136)
D(SLVN_LOG)	-0.064981	-0.039233	0.022939
	(0.03419)	(0.01766)	(0.00752)

4 Cointegrating Equation(s): Log likelihood 2083.962

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	HUN_LOG	LAT_LOG	POL_LOG	SLVK_LOG	SLVN_LOG
1.000000	0.000000	0.000000	0.000000	0.222981	1.348807	-3.367030
				(0.13917)	(0.27071)	(0.51682)
0.000000	1.000000	0.000000	0.000000	0.304965	-2.454216	2.648914
				(0.19285)	(0.37514)	(0.71621)
0.000000	0.000000	1.000000	0.000000	1.023756	5.771207	-16.33385
				(0.70609)	(1.37350)	(2.62222)
0.000000	0.000000	0.000000	1.000000	0.555161	-4.437044	6.683258
				(0.48624)	(0.94584)	(1.80575)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.522580	0.025886	0.098263	-0.009421
	(0.10434)	(0.05799)	(0.02062)	(0.02313)
D(CZ_LOG)	-0.056262	-0.359750	0.017731	0.157464
	(0.12990)	(0.07219)	(0.02567)	(0.02880)
D(HUN_LOG)	0.061458	0.053671	-0.004775	-0.009869
	(0.09160)	(0.05091)	(0.01810)	(0.02031)
D(LAT_LOG)	0.155850	0.172541	-0.025319	-0.103532
	(0.27906)	(0.15509)	(0.05514)	(0.06186)
D(POL_LOG)	-0.239691	-0.146787	0.031395	0.014968
	(0.20242)	(0.11250)	(0.04000)	(0.04487)
D(SLVK_LOG)	-0.115328	0.067287	0.017947	0.006244
	(0.10737)	(0.05967)	(0.02121)	(0.02380)
D(SLVN_LOG)	-0.025496	-0.011789	0.023065	0.024161
	(0.03718)	(0.02067)	(0.00735)	(0.00824)

5 Cointegrating Equation(s): Log likelihood 2089.201

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	HUN_LOG	LAT_LOG	POL_LOG	SLVK_LOG	SLVN_LOG

1.000000	0.000000	0.000000	0.000000	0.000000	0.956567	-2.226157
					(0.18746)	(0.34186)
0.000000	1.000000	0.000000	0.000000	0.000000	-2.990674	4.209259
					(0.47685)	(0.86962)
0.000000	0.000000	1.000000	0.000000	0.000000	3.970340	-11.09584
					(0.93797)	(1.71054)
0.000000	0.000000	0.000000	1.000000	0.000000	-5.413617	9.523723
					(1.14263)	(2.08377)
0.000000	0.000000	0.000000	0.000000	1.000000	1.759079	-5.116468
					(0.59693)	(1.08860)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.529106	0.014396	0.078145	-0.014229	0.005400
	(0.10420)	(0.05909)	(0.02985)	(0.02362)	(0.03064)
D(CZ_LOG)	-0.067637	-0.379778	-0.017337	0.149084	0.015845
	(0.12927)	(0.07331)	(0.03703)	(0.02930)	(0.03801)
D(HUN_LOG)	0.053500	0.039659	-0.029309	-0.015732	0.042464
	(0.09117)	(0.05170)	(0.02611)	(0.02067)	(0.02681)
D(LAT_LOG)	0.129176	0.125576	-0.107550	-0.123184	0.080258
	(0.27733)	(0.15727)	(0.07944)	(0.06287)	(0.08155)
D(POL_LOG)	-0.218031	-0.108650	0.098168	0.030925	-0.119706
	(0.20073)	(0.11383)	(0.05750)	(0.04550)	(0.05902)
D(SLVK_LOG)	-0.106558	0.082727	0.044982	0.012705	-0.008436
	(0.10695)	(0.06065)	(0.03063)	(0.02424)	(0.03145)
D(SLVN_LOG)	-0.024933	-0.010797	0.024801	0.024576	0.026135
	(0.03726)	(0.02113)	(0.01067)	(0.00845)	(0.01096)

6 Cointegrating Equation(s): Log likelihood 2092.410

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	HUN_LOG	LAT_LOG	POL_LOG	SLVK_LOG	SLVN_LOG
1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	-0.468451
						(0.07900)
0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	-1.286152
						(0.26743)
0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	-3.800273
						(0.31901)
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	-0.423884
						(0.50906)
0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	-1.884133
						(0.30540)
0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	-1.837516
						(0.11288)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.535276	0.018768	0.070782	-0.013911	0.009427	-0.145089
	(0.10577)	(0.06049)	(0.03707)	(0.02363)	(0.03290)	(0.07852)
D(CZ_LOG)	-0.051590	-0.391149	0.001814	0.148258	0.005370	0.204065
	(0.13101)	(0.07492)	(0.04591)	(0.02927)	(0.04075)	(0.09726)
D(HUN_LOG)	0.048362	0.043299	-0.035440	-0.015468	0.045817	-0.017852
	(0.09255)	(0.05293)	(0.03243)	(0.02067)	(0.02879)	(0.06871)
D(LAT_LOG)	0.225107	0.057597	0.006937	-0.128123	0.017636	0.015558
	(0.27708)	(0.15846)	(0.09710)	(0.06190)	(0.08620)	(0.20570)
D(POL_LOG)	-0.185303	-0.131842	0.137227	0.029240	-0.141071	0.089425
	(0.20312)	(0.11616)	(0.07118)	(0.04538)	(0.06319)	(0.15079)
D(SLVK_LOG)	-0.080962	0.064589	0.075530	0.011387	-0.025144	-0.284645
	(0.10777)	(0.06163)	(0.03777)	(0.02408)	(0.03353)	(0.08001)
D(SLVN_LOG)	-0.018575	-0.015303	0.032389	0.024248	0.021985	0.012319
	(0.03769)	(0.02156)	(0.01321)	(0.00842)	(0.01173)	(0.02798)

Cointegration among the 7 new EU countries and the 3 EMU countries

Cointegration Test (Model 6) Choise of the appropriate model for the cointegration test

Date: 06/24/04 Time: 20:48
Sample: 1993:01 2003:12
Included observations: 128
Series: CYP_LOG CZ_LOG FR_LOG GER_LOG HUN_LOG LAT_LOG NETH_LOG POL_LOG SLVK_LOG SLVN_LOG
Lags interval: 1 to 1

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	5	6	5	4	5
Max-Eig	4	2	2	2	2
Log Likelihood by Rank (rows) and Model (columns)					
0	3171.309	3171.309	3188.127	3188.127	3191.565
1	3209.529	3211.065	3227.155	3230.893	3234.267
2	3238.741	3245.923	3261.337	3265.077	3268.244
3	3264.042	3271.411	3286.539	3290.949	3294.103
4	3284.923	3293.546	3305.929	3316.012	3319.050
5	3302.958	3312.907	3322.962	3333.127	3335.818
6	3316.173	3329.593	3335.705	3348.734	3350.765
7	3323.770	3342.190	3348.011	3361.119	3363.141
8	3328.212	3349.203	3353.040	3367.520	3369.181
9	3329.576	3353.586	3354.432	3371.846	3372.178
10	3329.754	3354.621	3354.621	3373.020	3373.020
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	-47.98921	-47.98921	-48.09573	-48.09573	-47.99321
1	-48.27389	-48.28226	-48.39305	-48.43582	-48.34793
2	-48.41783	-48.49880	-48.61464	-48.64183	-48.56632
3	-48.50066	-48.56893	-48.69592	-48.71795	-48.65786
4	-48.51443	-48.58665	-48.68639	-48.78144*	-48.73516
5	-48.48373	-48.56105	-48.64003	-48.72074	-48.68466
6	-48.37770	-48.49365	-48.52664	-48.63647	-48.60570
7	-48.18390	-48.36234	-48.40642	-48.50186	-48.48657
8	-47.94081	-48.14380	-48.17251	-48.27376	-48.26845
9	-47.64962	-47.88415	-47.88175	-48.01322	-48.00278
10	-47.33990	-47.57220	-47.57220	-47.70343	-47.70343
Schwarz Criteria by Rank (rows) and Model (columns)					
0	-45.76106*	-45.76106*	-45.64476	-45.64476	-45.31943
1	-45.60011	-45.58620	-45.49645	-45.51695	-45.22852
2	-45.29843	-45.33483	-45.27242	-45.25505	-45.00128
3	-44.93562	-44.93705	-44.90806	-44.86325	-44.64719
4	-44.50376	-44.48686	-44.45291	-44.45883	-44.27886
5	-44.02743	-43.99335	-43.96092	-43.93022	-43.78274
6	-43.47577	-43.45803	-43.40190	-43.37804	-43.25815
7	-42.83635	-42.85881	-42.83605	-42.77552	-42.69338
8	-42.14762	-42.17237	-42.15650	-42.07950	-42.02963
9	-41.41081	-41.44480	-41.42012	-41.35106	-41.31833
10	-40.65546	-40.66494	-40.66494	-40.57335	-40.57335

ESTIMATION
VEC Model - (Model 4, lags 1)

Vector Error Correction Estimates
Date: 06/24/04 Time: 22:20
Sample(adjusted): 1993:03 2003:10
Included observations: 128 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
CYP_LOG(-1)	1.000000
CZ_LOG(-1)	0.534066
	(0.16926)
	[3.15525]
FR_LOG(-1)	-1.398932
	(0.59626)
	[-2.34619]
GER_LOG(-1)	4.765009
	(0.55853)
	[8.53140]
HUN_LOG(-1)	-1.247450
	(0.24252)
	[-5.14370]
LAT_LOG(-1)	-0.247049
	(0.06033)
	[-4.09471]
NETH_LOG(-1)	-1.099323
	(0.34398)
	[-3.19587]
POL_LOG(-1)	-0.081101
	(0.07685)
	[-1.05535]
SLVK_LOG(-1)	-0.270521
	(0.23753)
	[-1.13890]
SLVN_LOG(-1)	-0.040760
	(0.29630)
	[-0.13756]
@TREND(93:01)	0.005090
	(0.00128)
	[3.98173]
C	-8.646295

Error Correction:	D(CYP_LOG)	D(CZ_LOG)	D(FR_LOG)	D(GER_LOG)	D(HUN_LOG)	D(LAT_LOG)	D(NETH_LOG)	D(POL_LOG)	D(SLVK_LOG)	D(SLVN_LOG)
CointEq1	-0.060252	-0.060713	0.031829	-0.162816	0.060085	0.226107	0.040186	-0.105613	-0.014459	-0.015887
	(0.04629)	(0.06084)	(0.01844)	(0.01975)	(0.03762)	(0.11720)	(0.03587)	(0.08518)	(0.04646)	(0.01674)
	[-1.30158]	[-0.99799]	[1.72602]	[-8.24489]	[1.59703]	[1.92920]	[1.12022]	[-1.23990]	[-0.31123]	[-0.94882]
D(CYP_LOG(-1))	-0.557419	0.100754	0.024964	0.120211	-0.046147	-0.132721	-0.030639	0.027637	-0.010668	0.028917
	(0.07476)	(0.09825)	(0.02978)	(0.03189)	(0.06076)	(0.18929)	(0.05794)	(0.13757)	(0.07503)	(0.02704)
	[-7.45584]	[1.02548]	[0.83822]	[3.76921]	[-0.75946]	[-0.70117]	[-0.52883]	[0.20090]	[-0.14218]	[1.06936]
D(CZ_LOG(-1))	0.036618	-0.507777	-0.008127	0.062279	-0.053706	-0.331299	-0.020144	-0.029383	-0.001030	0.051434
	(0.05401)	(0.07098)	(0.02152)	(0.02304)	(0.04390)	(0.13675)	(0.04186)	(0.09939)	(0.05420)	(0.01954)
	[0.67795]	[-7.15359]	[-0.37770]	[2.70296]	[-1.22343]	[-2.42265]	[-0.48125]	[-0.29565]	[-0.01900]	[2.63280]
D(FR_LOG(-1))	-0.673211	0.279202	-0.410240	-0.024154	0.163602	0.572069	0.073571	0.240585	-0.319771	0.009624
	(0.21191)	(0.27848)	(0.08441)	(0.09040)	(0.17222)	(0.53651)	(0.16422)	(0.38992)	(0.21266)	(0.07665)
	[-3.17691]	[1.00258]	[-4.85983]	[-0.26720]	[0.94993]	[1.06627]	[0.44801]	[0.61701]	[-1.50369]	[0.12557]
D(GER_LOG(-1))	0.083197	0.405647	0.080853	-0.039562	-0.289083	0.102579	-0.022387	0.203443	0.280422	0.164804
	(0.19583)	(0.25735)	(0.07801)	(0.08354)	(0.15915)	(0.49580)	(0.15175)	(0.36033)	(0.19652)	(0.07083)
	[0.42485]	[1.57624]	[1.03646]	[-0.47358]	[-1.81637]	[0.20690]	[-0.14752]	[0.56460]	[1.42694]	[2.32678]
D(HUN_LOG(-1))	-0.191653	-0.179804	-0.059691	-0.054296	-0.330483	0.226926	-0.086833	-0.331296	-0.120620	-0.046259
	(0.10822)	(0.14222)	(0.04311)	(0.04617)	(0.08795)	(0.27400)	(0.08386)	(0.19913)	(0.10860)	(0.03914)
	[-1.77095]	[-1.26425]	[-1.38460]	[-1.17611]	[-3.75742]	[0.82821]	[-1.03540]	[-1.66371]	[-1.11064]	[-1.18179]
D(LAT_LOG(-1))	-0.041899	0.083689	-0.001202	-0.029287	-0.010514	-0.270082	-0.019894	0.022601	0.074149	0.017598
	(0.03572)	(0.04695)	(0.01423)	(0.01524)	(0.02903)	(0.09045)	(0.02768)	(0.06573)	(0.03585)	(0.01292)
	[-1.17287]	[1.78260]	[-0.08445]	[-1.92180]	[-0.36212]	[-2.98610]	[-0.71860]	[0.34384]	[2.06829]	[1.36195]
D(NETH_LOG(-1))	0.056452	-0.301356	0.020500	-0.185600	-0.126830	0.249839	-0.382036	-0.323507	-0.142249	-0.010904
	(0.11462)	(0.15063)	(0.04566)	(0.04890)	(0.09316)	(0.29020)	(0.08883)	(0.21091)	(0.11503)	(0.04146)
	[0.49251]	[-2.00060]	[0.44897]	[-3.79579]	[-1.36146]	[0.86092]	[-4.30099]	[-1.53387]	[-1.23665]	[-0.26301]
D(POL_LOG(-1))	0.057512	-0.045752	0.008212	-0.062291	0.079454	0.000712	0.067242	-0.276273	-0.117530	-0.038373
	(0.05488)	(0.07213)	(0.02186)	(0.02341)	(0.04461)	(0.13896)	(0.04253)	(0.10099)	(0.05508)	(0.01985)
	[1.04787]	[-0.63431]	[0.37562]	[-2.66052]	[1.78121]	[0.00512]	[1.58096]	[-2.73564]	[-2.13384]	[-1.93300]

D(SLVK_LOG(-1))	-0.006296	0.338103	0.019927	0.049396	-0.090603	-0.480378	-0.061977	-0.115461	-0.279811	0.014977
	(0.09342)	(0.12277)	(0.03721)	(0.03985)	(0.07592)	(0.23651)	(0.07239)	(0.17189)	(0.09375)	(0.03379)
	[-0.06739]	[2.75405]	[0.53550]	[1.23953]	[-1.19336]	[-2.03107]	[-0.85612]	[-0.67171]	[-2.98474]	[0.44327]
D(SLVN_LOG(-1))	0.373285	-1.033036	0.120814	-0.149757	0.298959	-0.381299	-0.085198	-0.900203	-0.063074	0.163858
	(0.24780)	(0.32565)	(0.09871)	(0.10571)	(0.20140)	(0.62739)	(0.19203)	(0.45596)	(0.24868)	(0.08963)
	[1.50639]	[-3.17219]	[1.22390]	[-1.41669]	[1.48443]	[-0.60776]	[-0.44367]	[-1.97428]	[-0.25364]	[1.82821]
C	0.002659	0.005928	0.002115	0.002026	0.008820	0.007938	0.002359	0.008226	0.006164	0.001655
	(0.00234)	(0.00307)	(0.00093)	(0.00100)	(0.00190)	(0.00592)	(0.00181)	(0.00431)	(0.00235)	(0.00085)
	[1.13629]	[1.92796]	[2.26960]	[2.02974]	[4.63815]	[1.33989]	[1.30109]	[1.91075]	[2.62528]	[1.95504]
R-squared	0.446264	0.439029	0.295239	0.504664	0.224022	0.238126	0.234268	0.187745	0.251206	0.141273
Adj. R-squared	0.393755	0.385834	0.228408	0.457693	0.150437	0.165879	0.161655	0.110721	0.180199	0.059842
Sum sq. resids	0.069903	0.120728	0.011093	0.012721	0.046174	0.448091	0.041979	0.236676	0.070399	0.009145
S.E. equation	0.024548	0.032261	0.009779	0.010472	0.019951	0.062152	0.019023	0.045170	0.024635	0.008879
F-statistic	8.498736	8.253127	4.417712	10.74406	3.044428	3.296006	3.226272	2.437486	3.537794	1.734886
Log likelihood	299.1868	264.2158	416.9996	408.2347	325.7278	180.2823	331.8226	221.1338	298.7344	429.3575
Akaike AIC	-4.487294	-3.940872	-6.328119	-6.191167	-4.901997	-2.629411	-4.997228	-3.267716	-4.480225	-6.521211
Schwarz SC	-4.219916	-3.673494	-6.060741	-5.923789	-4.634619	-2.362034	-4.729850	-3.000338	-4.212847	-6.253833
Mean dependent	0.000813	0.002759	0.001486	0.001281	0.006559	0.005363	0.001113	0.003127	0.003823	0.002069
S.D. dependent	0.031528	0.041165	0.011133	0.014220	0.021646	0.068052	0.020777	0.047899	0.027208	0.009157

Determinant Residual Covariance	1.51E-34
Log Likelihood	3230.893
Log Likelihood (d.f. adjusted)	3167.891
Akaike Information Criteria	-47.45142
Schwarz Criteria	-44.53255

VEC Model Equation

Estimation Proc:
===============================
EC(D,1) 1 1 CYP_LOG CZ_LOG FR_LOG GER_LOG HUN_LOG LAT_LOG NETH_LOG POL_LOG SLVK_LOG SLVN_LOG

VAR Model:
===============================
D(CYP_LOG) = A(1,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(1,1)*D(CYP_LOG(-1)) + C(1,2)*D(CZ_LOG(-1)) + C(1,3)*D(FR_LOG(-1)) + C(1,4)*D(GER_LOG(-1)) + C(1,5)*D(HUN_LOG(-1)) +
C(1,6)*D(LAT_LOG(-1)) + C(1,7)*D(NETH_LOG(-1)) + C(1,8)*D(POL_LOG(-1)) + C(1,9)*D(SLVK_LOG(-1)) + C(1,10)*D(SLVN_LOG(-1)) + C(1,11)

D(CZ_LOG) = A(2,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(2,1)*D(CYP_LOG(-1)) + C(2,2)*D(CZ_LOG(-1)) + C(2,3)*D(FR_LOG(-1)) + C(2,4)*D(GER_LOG(-1)) + C(2,5)*D(HUN_LOG(-1)) +
C(2,6)*D(LAT_LOG(-1)) + C(2,7)*D(NETH_LOG(-1)) + C(2,8)*D(POL_LOG(-1)) + C(2,9)*D(SLVK_LOG(-1)) + C(2,10)*D(SLVN_LOG(-1)) + C(2,11)

D(FR_LOG) = A(3,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(3,1)*D(CYP_LOG(-1)) + C(3,2)*D(CZ_LOG(-1)) + C(3,3)*D(FR_LOG(-1)) + C(3,4)*D(GER_LOG(-1)) + C(3,5)*D(HUN_LOG(-1)) +
C(3,6)*D(LAT_LOG(-1)) + C(3,7)*D(NETH_LOG(-1)) + C(3,8)*D(POL_LOG(-1)) + C(3,9)*D(SLVK_LOG(-1)) + C(3,10)*D(SLVN_LOG(-1)) + C(3,11)

D(GER_LOG) = A(4,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(4,1)*D(CYP_LOG(-1)) + C(4,2)*D(CZ_LOG(-1)) + C(4,3)*D(FR_LOG(-1)) + C(4,4)*D(GER_LOG(-1)) + C(4,5)*D(HUN_LOG(-1)) +
C(4,6)*D(LAT_LOG(-1)) + C(4,7)*D(NETH_LOG(-1)) + C(4,8)*D(POL_LOG(-1)) + C(4,9)*D(SLVK_LOG(-1)) + C(4,10)*D(SLVN_LOG(-1)) + C(4,11)

D(HUN_LOG) = A(5,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(5,1)*D(CYP_LOG(-1)) + C(5,2)*D(CZ_LOG(-1)) + C(5,3)*D(FR_LOG(-1)) + C(5,4)*D(GER_LOG(-1)) + C(5,5)*D(HUN_LOG(-1)) +
C(5,6)*D(LAT_LOG(-1)) + C(5,7)*D(NETH_LOG(-1)) + C(5,8)*D(POL_LOG(-1)) + C(5,9)*D(SLVK_LOG(-1)) + C(5,10)*D(SLVN_LOG(-1)) + C(5,11)

D(LAT_LOG) = A(6,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(6,1)*D(CYP_LOG(-1)) + C(6,2)*D(CZ_LOG(-1)) + C(6,3)*D(FR_LOG(-1)) + C(6,4)*D(GER_LOG(-1)) + C(6,5)*D(HUN_LOG(-1)) +
C(6,6)*D(LAT_LOG(-1)) + C(6,7)*D(NETH_LOG(-1)) + C(6,8)*D(POL_LOG(-1)) + C(6,9)*D(SLVK_LOG(-1)) + C(6,10)*D(SLVN_LOG(-1)) + C(6,11)

D(NETH_LOG) = A(7,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(7,1)*D(CYP_LOG(-1)) + C(7,2)*D(CZ_LOG(-1)) + C(7,3)*D(FR_LOG(-1)) + C(7,4)*D(GER_LOG(-1)) + C(7,5)*D(HUN_LOG(-1)) +
C(7,6)*D(LAT_LOG(-1)) + C(7,7)*D(NETH_LOG(-1)) + C(7,8)*D(POL_LOG(-1)) + C(7,9)*D(SLVK_LOG(-1)) + C(7,10)*D(SLVN_LOG(-1)) + C(7,11)

D(POL_LOG) = A(8,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(8,1)*D(CYP_LOG(-1)) + C(8,2)*D(CZ_LOG(-1)) + C(8,3)*D(FR_LOG(-1)) + C(8,4)*D(GER_LOG(-1)) + C(8,5)*D(HUN_LOG(-1)) +
C(8,6)*D(LAT_LOG(-1)) + C(8,7)*D(NETH_LOG(-1)) + C(8,8)*D(POL_LOG(-1)) + C(8,9)*D(SLVK_LOG(-1)) + C(8,10)*D(SLVN_LOG(-1)) + C(8,11)

D(SLVK_LOG) = A(9,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(9,1)*D(CYP_LOG(-1)) + C(9,2)*D(CZ_LOG(-1)) + C(9,3)*D(FR_LOG(-1)) + C(9,4)*D(GER_LOG(-1)) + C(9,5)*D(HUN_LOG(-1)) +
C(9,6)*D(LAT_LOG(-1)) + C(9,7)*D(NETH_LOG(-1)) + C(9,8)*D(POL_LOG(-1)) + C(9,9)*D(SLVK_LOG(-1)) + C(9,10)*D(SLVN_LOG(-1)) + C(9,11)

D(SLVN_LOG) = A(10,1)*(B(1,1)*CYP_LOG(-1) + B(1,2)*CZ_LOG(-1) + B(1,3)*FR_LOG(-1) + B(1,4)*GER_LOG(-1) + B(1,5)*HUN_LOG(-1) +
B(1,6)*LAT_LOG(-1) + B(1,7)*NETH_LOG(-1) + B(1,8)*POL_LOG(-1) + B(1,9)*SLVK_LOG(-1) + B(1,10)*SLVN_LOG(-1) + B(1,11)*(@TREND(93:01)) +
B(1,12)) + C(10,1)*D(CYP_LOG(-1)) + C(10,2)*D(CZ_LOG(-1)) + C(10,3)*D(FR_LOG(-1)) + C(10,4)*D(GER_LOG(-1)) + C(10,5)*D(HUN_LOG(-1)) +
C(10,6)*D(LAT_LOG(-1)) + C(10,7)*D(NETH_LOG(-1)) + C(10,8)*D(POL_LOG(-1)) + C(10,9)*D(SLVK_LOG(-1)) + C(10,10)*D(SLVN_LOG(-1)) +
C(10,11)

VAR Model - Substituted Coefficients:
===============================
D(CYP_LOG) = - 0.0602520948*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) -
1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-
1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) - 0.5574188659*D(CYP_LOG(-1)) +
0.03661790171*D(CZ_LOG(-1)) - 0.6732105642*D(FR_LOG(-1)) + 0.08319664046*D(GER_LOG(-1)) - 0.1916532181*D(HUN_LOG(-1)) -
0.04189938024*D(LAT_LOG(-1)) + 0.05645229858*D(NETH_LOG(-1)) + 0.0575121711*D(POL_LOG(-1)) - 0.006295536086*D(SLVK_LOG(-1)) +
0.3732848775*D(SLVN_LOG(-1)) + 0.002658706971

D(CZ_LOG) = - 0.06071310279*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) -
1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-
1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) + 0.100754449*D(CYP_LOG(-1)) -
0.507777034*D(CZ_LOG(-1)) + 0.2792016243*D(FR_LOG(-1)) + 0.4056465544*D(GER_LOG(-1)) - 0.179803776*D(HUN_LOG(-1)) +
0.08368857256*D(LAT_LOG(-1)) - 0.301356163*D(NETH_LOG(-1)) - 0.04575189915*D(POL_LOG(-1)) + 0.3381031074*D(SLVK_LOG(-1)) -
1.033036297*D(SLVN_LOG(-1)) + 0.005928323822

D(FR_LOG) = 0.0318286312*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) - 1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) + 0.02496390456*D(CYP_LOG(-1)) - 0.008126731354*D(CZ_LOG(-1)) - 0.4102397882*D(FR_LOG(-1)) + 0.08085276107*D(GER_LOG(-1)) - 0.05969062204*D(HUN_LOG(-1)) - 0.001201795307*D(LAT_LOG(-1)) + 0.02049988987*D(NETH_LOG(-1)) + 0.0082123212*D(POL_LOG(-1)) + 0.01992743283*D(SLVK_LOG(-1)) + 0.1208143214*D(SLVN_LOG(-1)) + 0.002115433765

D(GER_LOG) = - 0.1628156598*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) - 1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) + 0.1202109855*D(CYP_LOG(-1)) + 0.06227916097*D(CZ_LOG(-1)) - 0.02415378096*D(FR_LOG(-1)) - 0.03956183044*D(GER_LOG(-1)) - 0.05429591772*D(HUN_LOG(-1)) - 0.02928700257*D(LAT_LOG(-1)) - 0.1855997999*D(NETH_LOG(-1)) - 0.06229135945*D(POL_LOG(-1)) + 0.04939585557*D(SLVK_LOG(-1)) - 0.1497567119*D(SLVN_LOG(-1)) + 0.002025955951

D(HUN_LOG) = 0.0600848055*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) - 1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) - 0.04614664539*D(CYP_LOG(-1)) - 0.05370596657*D(CZ_LOG(-1)) + 0.1636017583*D(FR_LOG(-1)) - 0.2890834456*D(GER_LOG(-1)) - 0.330483039*D(HUN_LOG(-1)) - 0.01051368944*D(LAT_LOG(-1)) - 0.1268297677*D(NETH_LOG(-1)) + 0.07945377971*D(POL_LOG(-1)) - 0.09060298727*D(SLVK_LOG(-1)) + 0.2989585861*D(SLVN_LOG(-1)) + 0.008820105464

D(LAT_LOG) = 0.2261072901*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) - 1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) - 0.1327214864*D(CYP_LOG(-1)) - 0.331299235*D(CZ_LOG(-1)) + 0.5720694117*D(FR_LOG(-1)) + 0.1025790553*D(GER_LOG(-1)) + 0.2269261836*D(HUN_LOG(-1)) - 0.2700818387*D(LAT_LOG(-1)) + 0.2498394989*D(NETH_LOG(-1)) + 0.0007120257116*D(POL_LOG(-1)) - 0.480378074*D(SLVK_LOG(-1)) - 0.3812994244*D(SLVN_LOG(-1)) + 0.007937519282

D(NETH_LOG) = 0.0401861393*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) - 1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) - 0.03063874871*D(CYP_LOG(-1)) - 0.0201437051*D(CZ_LOG(-1)) + 0.07357055153*D(FR_LOG(-1)) - 0.02238670677*D(GER_LOG(-1)) - 0.08683343429*D(HUN_LOG(-1)) - 0.01989372194*D(LAT_LOG(-1)) - 0.3820359946*D(NETH_LOG(-1)) + 0.06724232377*D(POL_LOG(-1)) - 0.06197651532*D(SLVK_LOG(-1)) - 0.08519797918*D(SLVN_LOG(-1)) + 0.002359164804

D(POL_LOG) = - 0.105612834*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) - 1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) + 0.02763703903*D(CYP_LOG(-1)) - 0.02938341297*D(CZ_LOG(-1)) + 0.2405849251*D(FR_LOG(-1)) + 0.2034434871*D(GER_LOG(-1)) - 0.3312958975*D(HUN_LOG(-1)) + 0.02260146542*D(LAT_LOG(-1)) - 0.3235069881*D(NETH_LOG(-1)) - 0.2762731611*D(POL_LOG(-1)) - 0.11546092*D(SLVK_LOG(-1)) - 0.9002032999*D(SLVN_LOG(-1)) + 0.008226434014

D(SLVK_LOG) = - 0.01445850829*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) - 1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) - 0.01066757556*D(CYP_LOG(-1)) - 0.001030115344*D(CZ_LOG(-1)) - 0.3197706747*D(FR_LOG(-1)) + 0.2804218367*D(GER_LOG(-1)) - 0.1206202067*D(HUN_LOG(-1)) + 0.07414876614*D(LAT_LOG(-1)) - 0.1422491088*D(NETH_LOG(-1)) - 0.1175302324*D(POL_LOG(-1)) - 0.2798114327*D(SLVK_LOG(-1)) - 0.06307432799*D(SLVN_LOG(-1)) + 0.006164403115

D(SLVN_LOG) = - 0.01588654315*(CYP_LOG(-1) + 0.5340655177*CZ_LOG(-1) - 1.398932186*FR_LOG(-1) + 4.765009291*GER_LOG(-1) - 1.247450333*HUN_LOG(-1) - 0.2470494004*LAT_LOG(-1) - 1.09932254*NETH_LOG(-1) - 0.08110127686*POL_LOG(-1) - 0.2705205013*SLVK_LOG(-1) - 0.04076024806*SLVN_LOG(-1) + 0.005090408717*(@TREND(93:01)) - 8.646295183) + 0.02891673136*D(CYP_LOG(-1)) + 0.05143443655*D(CZ_LOG(-1)) + 0.009624229061*D(FR_LOG(-1)) + 0.1648036278*D(GER_LOG(-1)) - 0.04625854829*D(HUN_LOG(-1)) + 0.01759785907*D(LAT_LOG(-1)) - 0.01090363922*D(NETH_LOG(-1)) - 0.03837297003*D(POL_LOG(-1)) + 0.01497716313*D(SLVK_LOG(-1)) + 0.1638583681*D(SLVN_LOG(-1)) + 0.001654536546

Cointegration Test

Date: 06/24/04 Time: 22:42
Sample(adjusted): 1993:03 2003:10
Included observations: 128 after adjusting endpoints
Trend assumption: Linear deterministic trend (restricted)
Series: CYP_LOG CZ_LOG FR_LOG GER_LOG HUN_LOG LAT_LOG NETH_LOG POL_LOG SLVK_LOG SLVN_LOG
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.487381	369.7861	263.42	279.07
At most 1 **	0.413823	284.2536	222.21	234.41
At most 2 **	0.332518	215.8846	182.82	196.08
At most 3 **	0.324037	164.1414	146.76	158.49
At most 4	0.234652	114.0144	114.90	124.75
At most 5	0.216401	79.78416	87.31	96.58
At most 6	0.175937	48.57031	62.99	70.05
At most 7	0.095183	23.80128	42.44	48.45
At most 8	0.065360	10.99835	25.32	30.45
At most 9	0.018164	2.346334	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Trace test indicates 4 cointegrating equation(s) at both 5% and 1% levels

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.487381	85.53246	66.23	73.73
At most 1 **	0.413823	68.36905	61.29	67.88
At most 2	0.332518	51.74316	55.50	62.46
At most 3 *	0.324037	50.12698	49.42	54.71
At most 4	0.234652	34.23028	43.97	49.51
At most 5	0.216401	31.21385	37.52	42.36
At most 6	0.175937	24.76903	31.46	36.65
At most 7	0.095183	12.80293	25.54	30.34
At most 8	0.065360	8.652016	18.96	23.65
At most 9	0.018164	2.346334	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Max-eigenvalue test indicates 2 cointegrating equation(s) at both 5% and 1% levels

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
21.33475	11.39416	-29.84587	101.6603	-26.61405	-5.270738	-23.45378	-1.730276	-5.771488	-0.869610	0.108603
0.544213	-11.82110	74.19337	-34.49159	-26.78546	-7.036473	26.32507	4.075726	34.37835	-4.054850	-0.002829
28.13268	-27.22834	33.98621	27.03055	-35.32905	7.451590	-12.61135	4.727734	18.24551	-12.81933	0.153481
10.05901	-10.60136	78.41992	-38.62220	5.725177	4.727105	-66.88633	-4.393618	19.77429	-15.00577	-0.067821
3.711746	5.647078	-34.24915	33.61888	10.12266	2.707357	-1.649674	4.160519	9.561548	-58.53926	-0.021151
-18.74637	-10.75955	-39.63711	22.57805	15.47945	2.259525	14.66490	-9.400851	24.58427	-5.104768	-0.092312
-40.68519	-5.128057	27.58447	20.74500	-9.684209	-0.084387	-12.43510	3.691893	2.104889	13.31177	0.007588
-3.762791	-11.79869	-10.57661	10.52920	-9.738712	-3.011601	-5.111529	-6.867056	-13.13885	14.88301	0.160605
-0.704811	0.012204	22.18746	1.763125	-10.74509	1.752298	-6.282010	-5.197162	-4.498602	-19.61367	0.121443
3.222301	-2.719141	12.67868	6.478004	9.475291	-1.484596	4.972499	-2.206888	-2.268515	-10.48314	-0.049634

Unrestricted Adjustment Coefficients (alpha):

D(CYP_LOG)	-0.002824	-0.002302	-0.004058	1.34E-05	0.000513	-0.000315	0.008944	0.001045	-0.000459	-0.000284
D(CZ_LOG)	-0.002846	-0.005928	0.012945	-0.003290	-0.001511	0.005652	0.002771	0.002173	-0.001903	0.000340
D(FR_LOG)	0.001492	-0.002608	0.001019	-0.002117	0.001835	-0.000934	-0.000508	0.000662	-0.000176	-0.000687
D(GER_LOG)	-0.007631	-0.000283	0.000518	-0.000603	-6.54E-05	-0.002396	-0.000871	0.000210	0.000320	-0.000238
D(HUN_LOG)	0.002816	0.005337	0.005167	-0.001876	-7.27E-05	-0.004732	0.001935	0.001753	0.001475	-0.000195
D(LAT_LOG)	0.010598	0.006670	-0.002442	-0.002776	0.008401	-0.003202	-0.002691	0.012508	-0.006272	0.003297
D(NETH_LOG)	0.001884	-0.005562	0.002298	0.007510	0.003137	-0.001552	0.000538	0.000420	-0.000245	-0.000193
D(POL_LOG)	-0.004950	-0.003311	-0.000569	-0.000771	6.96E-05	0.003862	-0.002739	0.009116	0.007215	-0.000482
D(SLVK_LOG)	-0.000678	-0.009473	-0.001225	-0.001786	-0.004027	-0.003514	-0.000721	0.001815	0.002065	0.001274
D(SLVN_LOG)	-0.000745	-0.001157	0.000719	-0.001437	0.002987	-0.000133	0.000608	3.92E-05	0.000509	0.000531

1 Cointegrating Equation(s): Log likelihood 3230.893

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.534066	-1.398932	4.765009	-1.247450	-0.247049	-1.099323	-0.081101	-0.270521	-0.040760	0.005090
	(0.16926)	(0.59626)	(0.55853)	(0.24252)	(0.06033)	(0.34398)	(0.07685)	(0.23753)	(0.29630)	(0.00128)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.060252
	(0.04629)
D(CZ_LOG)	-0.060713
	(0.06084)
D(FR_LOG)	0.031829
	(0.01844)
D(GER_LOG)	-0.162816
	(0.01975)
D(HUN_LOG)	0.060085
	(0.03762)

D(LAT_LOG)	0.226107
	(0.11720)
D(NETH_LOG)	0.040186
	(0.03587)
D(POL_LOG)	-0.105613
	(0.08518)
D(SLVK_LOG)	-0.014459
	(0.04646)
D(SLVN_LOG)	-0.015887
	(0.01674)

2 Cointegrating Equation(s): Log likelihood 3265.077

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.000000	1.906182	3.129762	-2.398616	-0.551393	0.087858	0.100563	1.251879	-0.218580	0.004844
		(0.73354)	(0.79836)	(0.32079)	(0.08210)	(0.49972)	(0.11235)	(0.27535)	(0.43388)	(0.00181)
0.000000	1.000000	-6.188594	3.061884	2.155476	0.569862	-2.222911	-0.340154	-2.850586	0.332955	0.000462
		(1.02423)	(1.11473)	(0.44791)	(0.11464)	(0.69774)	(0.15687)	(0.38446)	(0.60581)	(0.00252)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.061505	-0.004964
	(0.04608)	(0.03545)
D(CZ_LOG)	-0.063939	0.037652
	(0.05971)	(0.04594)
D(FR_LOG)	0.030409	0.047825
	(0.01771)	(0.01362)
D(GER_LOG)	-0.162970	-0.083607
	(0.01975)	(0.01519)
D(HUN_LOG)	0.062989	-0.031001
	(0.03612)	(0.02779)
D(LAT_LOG)	0.229737	0.041906
	(0.11649)	(0.08962)
D(NETH_LOG)	0.037159	0.087207
	(0.03415)	(0.02627)
D(POL_LOG)	-0.107415	-0.017265
	(0.08495)	(0.06536)
D(SLVK_LOG)	-0.019614	0.104254
	(0.04251)	(0.03270)
D(SLVN_LOG)	-0.016516	0.005196
	(0.01659)	(0.01276)

3 Cointegrating Equation(s): Log likelihood 3290.949

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.000000	0.000000	3.356221	-1.478270	-0.161533	-0.678174	0.025963	0.293545	-0.194308	0.005146
			(0.36720)	(0.17103)	(0.04417)	(0.25694)	(0.05972)	(0.14496)	(0.23709)	(0.00097)
0.000000	1.000000	0.000000	2.326667	-0.832512	-0.695854	0.264079	-0.097958	0.260731	0.254153	-0.000518
			(0.71065)	(0.33100)	(0.08548)	(0.49727)	(0.11559)	(0.28054)	(0.45885)	(0.00188)
0.000000	0.000000	1.000000	-0.118802	-0.482822	-0.204524	0.401867	0.039136	0.502750	-0.012733	-0.000158
			(0.23157)	(0.10786)	(0.02785)	(0.16204)	(0.03767)	(0.09142)	(0.14952)	(0.00061)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.175667	0.105528	-0.224435
	(0.07508)	(0.06760)	(0.18474)
D(CZ_LOG)	0.300228	-0.314809	0.085047
	(0.08922)	(0.08033)	(0.21954)
D(FR_LOG)	0.059087	0.020069	-0.203360
	(0.02911)	(0.02621)	(0.07163)
D(GER_LOG)	-0.148403	-0.097706	0.224360
	(0.03263)	(0.02938)	(0.08029)
D(HUN_LOG)	0.208340	-0.171679	0.487512
	(0.05731)	(0.05160)	(0.14103)
D(LAT_LOG)	0.161042	0.108393	0.095591
	(0.19258)	(0.17340)	(0.47390)
D(NETH_LOG)	0.101798	0.024646	-0.390766
	(0.05600)	(0.05042)	(0.13781)
D(POL_LOG)	-0.123421	-0.001773	-0.117242
	(0.14055)	(0.12655)	(0.34586)
D(SLVK_LOG)	-0.054068	0.137601	-0.724196
	(0.07022)	(0.06323)	(0.17280)
D(SLVN_LOG)	0.003710	-0.014380	-0.039202
	(0.02735)	(0.02463)	(0.06730)

4 Cointegrating Equation(s): Log likelihood 3316.012

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.000000	0.000000	0.000000	2.859642	1.150684	-8.437591	-0.739872	-1.440495	-1.012234	-0.004700
				(0.56248)	(0.19366)	(1.07757)	(0.26505)	(0.64192)	(1.03983)	(0.00387)
0.000000	1.000000	0.000000	0.000000	2.174703	0.213828	-5.115061	-0.628866	-0.941376	-0.312866	-0.007344
				(0.37276)	(0.12834)	(0.71411)	(0.17565)	(0.42541)	(0.68910)	(0.00256)
0.000000	0.000000	1.000000	0.000000	-0.636373	-0.250973	0.676531	0.066245	0.564131	0.016219	0.000190
				(0.09545)	(0.03286)	(0.18287)	(0.04498)	(0.10894)	(0.17646)	(0.00066)
0.000000	0.000000	0.000000	1.000000	-1.292499	-0.390981	2.311951	0.228184	0.516665	0.243705	0.002934
				(0.17782)	(0.06122)	(0.34066)	(0.08379)	(0.20294)	(0.32873)	(0.00122)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.175533	0.105387	-0.223386	-0.317902
	(0.07806)	(0.07126)	(0.24885)	(0.24928)
D(CZ_LOG)	0.267129	-0.279925	-0.172993	0.392157
	(0.09209)	(0.08406)	(0.29356)	(0.29406)
D(FR_LOG)	0.037790	0.042515	-0.369394	0.350936
	(0.02939)	(0.02683)	(0.09370)	(0.09386)
D(GER_LOG)	-0.154472	-0.091310	0.177049	-0.728756

	(0.03386)	(0.03091)	(0.10795)	(0.10813)
D(HUN_LOG)	0.189466	-0.151787	0.340370	0.314346
	(0.05925)	(0.05408)	(0.18887)	(0.18919)
D(LAT_LOG)	0.133122	0.137819	-0.122077	0.888534
	(0.20002)	(0.18259)	(0.63764)	(0.63872)
D(NETH_LOG)	0.177345	-0.054974	0.198192	0.155359
	(0.05230)	(0.04774)	(0.16672)	(0.16700)
D(POL_LOG)	-0.131173	0.006397	-0.177678	-0.374661
	(0.14612)	(0.13338)	(0.46581)	(0.46660)
D(SLVK_LOG)	-0.072035	0.156536	-0.864263	0.293707
	(0.07276)	(0.06642)	(0.23196)	(0.23236)
D(SLVN_LOG)	-0.010744	0.000853	-0.151886	0.039147
	(0.02801)	(0.02557)	(0.08930)	(0.08945)

5 Cointegrating Equation(s): Log likelihood 3333.127

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.000000	0.000000	0.000000	0.000000	0.578577	-9.724728	-2.367032	-8.577896	18.50937	0.012792
					(0.60271)	(3.42443)	(0.88772)	(2.31464)	(3.34261)	(0.00983)
0.000000	1.000000	0.000000	0.000000	0.000000	-0.221248	-6.093904	-1.866290	-6.369232	14.53294	0.005959
					(0.44852)	(2.54840)	(0.66062)	(1.72252)	(2.48752)	(0.00732)
0.000000	0.000000	1.000000	0.000000	0.000000	-0.123659	0.962965	0.428346	2.152459	-4.328039	-0.003703
					(0.13340)	(0.75793)	(0.19648)	(0.51230)	(0.73982)	(0.00218)
0.000000	0.000000	0.000000	1.000000	0.000000	-0.132400	2.893710	0.963626	3.742622	-8.579654	-0.004973
					(0.26511)	(1.50630)	(0.39048)	(1.01814)	(1.47031)	(0.00432)
0.000000	0.000000	0.000000	0.000000	1.000000	0.200062	0.450104	0.569008	2.495907	-6.826589	-0.006117
					(0.19903)	(1.13085)	(0.29315)	(0.76437)	(1.10384)	(0.00325)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.173627	0.108286	-0.240969	-0.300643	0.285465
	(0.07844)	(0.07224)	(0.25922)	(0.25926)	(0.11266)
D(CZ_LOG)	0.261521	-0.288457	-0.121246	0.341362	-0.256931
	(0.09241)	(0.08511)	(0.30539)	(0.30543)	(0.13272)
D(FR_LOG)	0.044601	0.052878	-0.432244	0.412630	0.000586
	(0.02887)	(0.02659)	(0.09539)	(0.09541)	(0.04146)
D(GER_LOG)	-0.154715	-0.091679	0.179289	-0.730956	0.188279
	(0.03403)	(0.03135)	(0.11247)	(0.11249)	(0.04888)
D(HUN_LOG)	0.189196	-0.152198	0.342861	0.311902	-0.411918
	(0.05955)	(0.05484)	(0.19679)	(0.19681)	(0.08552)
D(LAT_LOG)	0.164304	0.185260	-0.409800	1.170962	-0.305308
	(0.19897)	(0.18325)	(0.65753)	(0.65762)	(0.28576)
D(NETH_LOG)	0.188989	-0.037258	0.090745	0.260828	0.092422
	(0.05145)	(0.04739)	(0.17004)	(0.17006)	(0.07390)
D(POL_LOG)	-0.130915	0.006790	-0.180063	-0.372319	0.236826
	(0.14686)	(0.13526)	(0.48534)	(0.48540)	(0.21093)
D(SLVK_LOG)	-0.086980	0.133798	-0.726359	0.158340	0.264046
	(0.07182)	(0.06615)	(0.23735)	(0.23738)	(0.10315)
D(SLVN_LOG)	0.000341	0.017719	-0.254175	0.139554	0.047421
	(0.02623)	(0.02416)	(0.08668)	(0.08669)	(0.03767)

6 Cointegrating Equation(s): Log likelihood 3348.734

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	17.33445	6.483461	15.97421	-44.86042	-0.014720
						(7.58300)	(2.01577)	(5.38723)	(7.61008)	(0.02258)
0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	-16.44136	-5.250727	-15.75798	38.76560	0.016480
						(6.49577)	(1.72675)	(4.61482)	(6.51897)	(0.01934)
0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	-4.820373	-1.463263	-3.095044	9.215937	0.002178
						(1.61455)	(0.42919)	(1.14703)	(1.62032)	(0.00481)
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	-3.298444	-1.061698	-1.875819	5.921725	0.001323
						(1.07389)	(0.28547)	(0.76293)	(1.07772)	(0.00320)
0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	9.806726	3.629364	10.98562	-28.73882	-0.015630
						(4.75773)	(1.26473)	(3.38005)	(4.77471)	(0.01417)
0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	-46.76850	-15.29700	-42.43532	109.5269	0.047551
						(18.6017)	(4.94482)	(13.2153)	(18.6681)	(0.05539)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.167724	0.111674	-0.228486	-0.307753	0.280591	0.001588
	(0.08797)	(0.07577)	(0.27255)	(0.26364)	(0.11735)	(0.02751)
D(CZ_LOG)	0.155568	-0.349269	-0.345271	0.468972	-0.169442	0.146296
	(0.10135)	(0.08729)	(0.31398)	(0.30372)	(0.13519)	(0.03170)
D(FR_LOG)	0.062119	0.062932	-0.395205	0.391532	-0.013878	0.010931
	(0.03218)	(0.02771)	(0.09969)	(0.09643)	(0.04292)	(0.01006)
D(GER_LOG)	-0.109797	-0.065899	0.274262	-0.785054	0.151189	0.037631
	(0.03705)	(0.03191)	(0.11477)	(0.11102)	(0.04942)	(0.01159)
D(HUN_LOG)	0.277902	-0.101285	0.530419	0.205065	-0.485165	-0.033657
	(0.06427)	(0.05535)	(0.19910)	(0.19259)	(0.08573)	(0.02010)
D(LAT_LOG)	0.224327	0.219710	-0.282887	1.098671	-0.354871	-0.118602
	(0.22283)	(0.19192)	(0.69033)	(0.66777)	(0.29725)	(0.06969)
D(NETH_LOG)	0.218088	-0.020557	0.152271	0.225782	0.068395	0.086816
	(0.05740)	(0.04944)	(0.17784)	(0.17203)	(0.07657)	(0.01795)
D(POL_LOG)	-0.203314	-0.034764	-0.333143	-0.285122	0.296608	0.050421
	(0.16406)	(0.14130)	(0.50825)	(0.49164)	(0.21884)	(0.05131)
D(SLVK_LOG)	-0.021103	0.171609	-0.587069	0.078998	0.209649	0.033814
	(0.07942)	(0.06840)	(0.24604)	(0.23799)	(0.10594)	(0.02484)
D(SLVN_LOG)	0.002839	0.019152	-0.248894	0.136546	0.045359	0.018417
	(0.02942)	(0.02534)	(0.09113)	(0.08815)	(0.03924)	(0.00920)

7 Cointegrating Equation(s): Log likelihood 3361.119

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.003349	0.614232	-1.392106	-0.000450
							(0.07093)	(0.17938)	(0.24777)	(0.00070)

0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.895521	-1.189368	-2.463166	0.002945
							(0.20775)	(0.52536)	(0.72568)	(0.00206)
0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.338730	1.176266	-2.871752	-0.001791
							(0.12316)	(0.31145)	(0.43020)	(0.00122)
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.171354	1.046916	-2.349535	-0.001392
							(0.09696)	(0.24520)	(0.33869)	(0.00096)
0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	-0.036669	2.295929	-4.147229	-0.007557
							(0.17640)	(0.44608)	(0.61617)	(0.00175)
0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	2.186396	-0.993975	-7.750913	0.009051
							(0.49291)	(1.24648)	(1.72176)	(0.00488)
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.373828	0.886095	-2.507625	-0.000823
							(0.11155)	(0.28210)	(0.38967)	(0.00111)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.531612	0.065809	0.018229	-0.122209	0.193975	0.000833	-0.060772
	(0.11355)	(0.07047)	(0.25662)	(0.24605)	(0.10967)	(0.02533)	(0.15465)
D(CZ_LOG)	0.042819	-0.363480	-0.268828	0.526461	-0.196279	0.146062	0.018441
	(0.14132)	(0.08770)	(0.31938)	(0.30623)	(0.13650)	(0.03152)	(0.19247)
D(FR_LOG)	0.082790	0.065538	-0.409220	0.380992	-0.008958	0.010973	0.014707
	(0.04503)	(0.02795)	(0.10178)	(0.09759)	(0.04350)	(0.01005)	(0.06133)
D(GER_LOG)	-0.074341	-0.061430	0.250223	-0.803133	0.159629	0.037705	0.181163
	(0.05173)	(0.03210)	(0.11692)	(0.11210)	(0.04997)	(0.01154)	(0.07046)
D(HUN_LOG)	0.199175	-0.111208	0.583795	0.245207	-0.503904	-0.033820	0.041454
	(0.08951)	(0.05555)	(0.20229)	(0.19396)	(0.08645)	(0.01997)	(0.12191)
D(LAT_LOG)	0.333815	0.233510	-0.357120	1.042844	-0.328810	-0.118375	0.116130
	(0.31211)	(0.19369)	(0.70536)	(0.67631)	(0.30146)	(0.06962)	(0.42508)
D(NETH_LOG)	0.196186	-0.023317	0.167120	0.236949	0.063181	0.086770	-0.756534
	(0.08044)	(0.04992)	(0.18179)	(0.17430)	(0.07769)	(0.01794)	(0.10955)
D(POL_LOG)	-0.091858	-0.020715	-0.408710	-0.341952	0.323138	0.050652	0.178251
	(0.22956)	(0.14246)	(0.51881)	(0.49744)	(0.22173)	(0.05121)	(0.31265)
D(SLVK_LOG)	0.008239	0.175307	-0.606963	0.064037	0.216633	0.033875	-0.134481
	(0.11129)	(0.06906)	(0.25151)	(0.24115)	(0.10749)	(0.02482)	(0.15157)
D(SLVN_LOG)	-0.021886	0.016036	-0.232131	0.149153	0.039474	0.018366	0.059606
	(0.04112)	(0.02552)	(0.09292)	(0.08910)	(0.03971)	(0.00917)	(0.05600)

8 Cointegrating Equation(s): Log likelihood 3367.520

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.614121	-1.367137	-0.000484
								(0.17275)	(0.24205)	(0.00064)
0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	-1.219092	4.213142	-0.006178
								(0.82925)	(1.16193)	(0.00307)
0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.165023	-0.346448	-0.005241
								(0.27564)	(0.38622)	(0.00102)
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.041228	-1.072051	-0.003138
								(0.18059)	(0.25304)	(0.00067)
0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	2.297146	-4.420607	-0.007184
								(0.45842)	(0.64233)	(0.00170)
0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	-1.066546	8.549151	-0.013222
								(2.02197)	(2.83314)	(0.00749)
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.873687	0.279348	-0.004631
								(0.31500)	(0.44138)	(0.00117)
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.033192	-7.455221	0.010187
								(1.25500)	(1.75848)	(0.00465)

Adjustment coefficients (std.err. in parentheses)

D(CYP_LOG)	-0.535546	0.053474	0.007173	-0.111202	0.183794	-0.002315	-0.066116	0.007197
	(0.11365)	(0.07406)	(0.25714)	(0.24661)	(0.11118)	(0.02597)	(0.15478)	(0.02949)
D(CZ_LOG)	0.034643	-0.389117	-0.291809	0.549340	-0.217440	0.139518	0.007334	-0.007690
	(0.14113)	(0.09197)	(0.31932)	(0.30625)	(0.13807)	(0.03225)	(0.19221)	(0.03662)
D(FR_LOG)	0.080298	0.057724	-0.416224	0.387964	-0.015407	0.008979	0.011321	0.010908
	(0.04499)	(0.02932)	(0.10179)	(0.09762)	(0.04401)	(0.01028)	(0.06127)	(0.01167)
D(GER_LOG)	-0.075132	-0.063911	0.247999	-0.800919	0.157581	0.037071	0.180089	0.034741
	(0.05183)	(0.03378)	(0.11727)	(0.11247)	(0.05070)	(0.01185)	(0.07059)	(0.01345)
D(HUN_LOG)	0.192580	-0.131886	0.565259	0.263660	-0.520972	-0.039098	0.032495	0.088840
	(0.08920)	(0.05813)	(0.20181)	(0.19355)	(0.08726)	(0.02038)	(0.12148)	(0.02314)
D(LAT_LOG)	0.286749	0.085928	-0.489417	1.174547	-0.450625	-0.156045	0.052193	-0.021279
	(0.30538)	(0.19901)	(0.69095)	(0.66266)	(0.29875)	(0.06979)	(0.41591)	(0.07924)
D(NETH_LOG)	0.194608	-0.028268	0.162682	0.241367	0.059095	0.085507	-0.758679	-0.021311
	(0.08057)	(0.05251)	(0.18231)	(0.17484)	(0.07882)	(0.01841)	(0.10974)	(0.02091)
D(POL_LOG)	-0.126160	-0.128274	-0.505128	-0.245966	0.234358	0.023198	0.131654	-0.112965
	(0.22472)	(0.14644)	(0.50843)	(0.48762)	(0.21983)	(0.05136)	(0.30605)	(0.05831)
D(SLVK_LOG)	0.001409	0.153890	-0.626162	0.083149	0.198956	0.028409	-0.143760	-0.034221
	(0.11109)	(0.07239)	(0.25135)	(0.24106)	(0.10868)	(0.02539)	(0.15130)	(0.02882)
D(SLVN_LOG)	-0.022033	0.015573	-0.232546	0.149566	0.039092	0.018248	0.059405	0.021937
	(0.04120)	(0.02685)	(0.09322)	(0.08941)	(0.04031)	(0.00942)	(0.05611)	(0.01069)

9 Cointegrating Equation(s): Log likelihood 3371.846

Normalized cointegrating coefficients (std.err. in parentheses)

CYP_LOG	CZ_LOG	FR_LOG	GER_LOG	HUN_LOG	LAT_LOG	NETH_LOG	POL_LOG	SLVK_LOG	SLVN_LOG	@TREND(93:02)
1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	140.8220	-0.274291
									(32.7281)	(0.06930)
0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	-278.0465	0.537357
									(64.3041)	(0.13617)
0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	269.3946	-0.524669
									(62.4251)	(0.13219)
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	240.0065	-0.467371
									(55.6628)	(0.11787)
0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	527.4439	-1.031370
									(122.392)	(0.25917)
0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	-238.3912	0.462300
									(55.0055)	(0.11648)
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	202.5666	-0.394167
									(46.9279)	(0.09937)

	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.229786	-0.004612
										(1.15393)	(0.00244)
	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	-231.5328	0.445852
										(53.4077)	(0.11309)
Adjustment coefficients (std.err. in parentheses)											
D(CYP_LOG)	-0.535222	0.053469	-0.003014	-0.112012	0.188727	-0.003120	-0.063231	0.009583	-0.132299		
	(0.11363)	(0.07404)	(0.26070)	(0.24657)	(0.11312)	(0.02619)	(0.15523)	(0.03118)	(0.10396)		
D(CZ_LOG)	0.035984	-0.389141	-0.334042	0.545984	-0.196988	0.136183	0.019292	0.002202	0.094089		
	(0.14077)	(0.09172)	(0.32297)	(0.30546)	(0.14013)	(0.03245)	(0.19230)	(0.03863)	(0.12879)		
D(FR_LOG)	0.080422	0.057722	-0.420131	0.387654	-0.013515	0.008670	0.012428	0.011823	-0.135934		
	(0.04498)	(0.02931)	(0.10320)	(0.09761)	(0.04478)	(0.01037)	(0.06145)	(0.01234)	(0.04116)		
D(GER_LOG)	-0.075357	-0.063907	0.255094	-0.800355	0.154145	0.037632	0.178080	0.033079	-0.033738		
	(0.05181)	(0.03376)	(0.11886)	(0.11242)	(0.05157)	(0.01194)	(0.07077)	(0.01422)	(0.04740)		
D(HUN_LOG)	0.191541	-0.131868	0.597987	0.266261	-0.536821	-0.036513	0.023229	0.081174	0.081775		
	(0.08885)	(0.05789)	(0.20384)	(0.19279)	(0.08845)	(0.02048)	(0.12137)	(0.02438)	(0.08129)		
D(LAT_LOG)	0.291169	0.085851	-0.628566	1.163490	-0.383237	-0.167034	0.091591	0.011315	-0.071481		
	(0.30352)	(0.19778)	(0.69638)	(0.65864)	(0.30216)	(0.06996)	(0.41464)	(0.08329)	(0.27771)		
D(NETH_LOG)	0.194780	-0.028271	0.157247	0.240935	0.061728	0.085078	-0.757140	-0.020038	-0.023080		
	(0.08057)	(0.05250)	(0.18485)	(0.17484)	(0.08021)	(0.01857)	(0.11007)	(0.02211)	(0.07372)		
D(POL_LOG)	-0.131245	-0.128186	-0.345046	-0.233245	0.156832	0.035841	0.086329	-0.150462	-0.173264		
	(0.22133)	(0.14422)	(0.50780)	(0.48028)	(0.22033)	(0.05102)	(0.30236)	(0.06073)	(0.20250)		
D(SLVK_LOG)	-4.65E-05	0.153916	-0.580336	0.086791	0.176763	0.032028	-0.156735	-0.044956	-0.538954		
	(0.11054)	(0.07203)	(0.25361)	(0.23986)	(0.11004)	(0.02548)	(0.15101)	(0.03033)	(0.10114)		
D(SLVN_LOG)	-0.022392	0.015579	-0.221249	0.150464	0.033621	0.019140	0.056206	0.019290	-0.027029		
	(0.04111)	(0.02679)	(0.09433)	(0.08922)	(0.04093)	(0.00948)	(0.05617)	(0.01128)	(0.03762)		