Comovements and Correlations in International Stock Markets

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1 Introduction

The existence of uncorrelated returns in international stock markets is fundamental in a context of global portfolio diversification. In presence of high stock market volatility, risk management represents the main aim for portfolio managers and international diversification is the key to achieve it. Since the first work by Solnik (1974) up to some recent papers such as Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998), evidence on the advantages of cross-country diversification has been the focus of extensive research. Many investors believe that cross-border diversification increases risk while most of the literature on this topic provides evidence of its value as a risk reducer.

Numerous studies have investigated international diversification using various methodologies and dataset. Starting from the early studies by Grubel (1968) and Levy and Sarnat (1970) ending with the work by Longin and Solnik (2001) have shown different results on this issue. The early works in the 70s witnessed that correlations among national stock market returns were low and national markets were largely responding to domestic economic fundamentals. In the eighties the use of stochastic calculus to analyse financial markets brought evidence of high and statistically significant level of interdependence between national markets. The hypothesis that global markets were becoming more integrated could be verified.

In the last decade, recent studies using larger dataset, have shown some interesting results, supporting partially both findings. The main assumption is that certain global *extreme events*, i.e. the 1987's stock market crash, the Kuwait's invasion by Iraq, the terrorism's attack in 2001, tend to move world equity markets in the same direction, thus reducing the effectiveness of international diversification. On the other hand, in the absence of global events national markets are dominated by domestic fundamentals and international investing increases the benefits of diversification. In this paper we want to investigate this assumption using the common trend and common cycle methodology developed by Vahid and Engle(1993) .

The idea of testing if a set of economic variables move together and identifying possible comovements among time series has a long history in economics. Recent econometric application study the common components in time series using cointegration and common trends as in Granger (1983) Engle and Granger (1987), Stock and Watson (1988), common features (Engle and Kozicki 1993) and codependency (Gourieaux et al. 1991). Comovements among time series indicate the existence of common components which would imply a reduction to a more parsimonious and probably more informative structure. An indicator of comovements among non stationary variables is cointegration, when the variables are cointegrated they share some common stochastic trends that drive their long run swings and at least one linear combination of them exists which has no long swings, i.e. it is stationary.

This methodology has been widely applied to understand the dynamic of macroeconomic phenomena, i.e. to investigate to what extent business cycles are transmitted from one country to another, while, in our knowledge, little evidence of its application to financial data could be found.

Hecq (2000), Mills (2002) and Sharma et. al (2002) are the only examples of application of such methodology to decompose a financial time series using the Beveridge-Nelson approach. Hecq studies the nature of the relationship between five major international stock market indices trying to identify a long run component and a cyclical component, and controls the presence of external shocks using dummy variables. He uses quarterly data in real US dollars taking the third observation of monthly data in order to avoid conditional heteroskedasticity problem. In our opinion this approach is not correct when trying to analyze financial time series which do not show the usual features of economic time series, i.e. no seasonality could be detected.

Mills sets up a VECM framework to investigate the presence of common trend and common cycles of the UK financial markets. He uses weekly data for the period '69-95. Sharma et al. analyze the degree of long term and short term comovements in the stock markets of five Asean countries trying to shed some light on the long-term and short-term market efficiency/inefficiency in the region.

In this paper we try to extend Mills' and Sharma' approach to analyze stock market indices for U.K., the U.S., Canada and Japan and to identify possible common cycles and common trend. This may lead us to provide a theoretical approach to support the idea that stock markets may have some "imitative behaviour" in the short run (the cyclical component) due to some extreme-global event, but in the long run a random walk component (the trend component) the markets' dynamic.

For portfolio managers, who follow a top-down approach, typically first diversifying across countries and then choosing the best stocks in each market, our approach results useful. First, it shows that, exploiting information on stocks' exposure to different sources of systematic risk, country-specific shocks are by far the most important source of international return variation. International diversification strategies that are based on cross-country diversification therefore still proves to be effective. Second, our approach provides portfolio managers with information on which stocks to pick within countries. Because stocks differ in their exposure to country-specific shocks, not all diversified country portfolios are equal in terms of risk reduction.

The rest of the paper is organized as follows. In section 2 a brief review of the extensive literature on markets diversification is provided; in section 2 a description of the methodology used is provided, recalling the main feature of the VECM framework and the properties of the multivariate version of the Beveridge-Nelson trend-cycle decomposition. In section 4, a description of the data set used and the resulting common trends for the four international stock markets is provided. Section 5 concludes and provides suggestion for further applications.

2 Market Integration

The advances in computer technology together with increasing financial deregulation have led to more integrated world stock markets. The stock markets integration has interested various scholars at different extents. For example the early studies by Grubel (1968), Levy and Sarnat(1970), Grubel and Fadner (1968), Agmon (1972, 1973), Ripley (1973) and Solnik(1974) analyzed the benefits of international portfolio diversification. All these studies, using different methodologies and data set from a variety of countries, agreed that correlations among national stock markets returns were low and that national speculative markets were largely responding to domestic economic fundamentals.

The use of continuous time stochastic processes and the arbitrage pricing theory, have been used in recent empirical studies, aimed at testing interdependencies between the time series of national stock market returns. Hilliard(1979), Christofi and Philippatos(1987), Grauer and Hakansson (1987), Schollhammer and Sand (1987), Wheatley(1988), Eun and Shim(1989), French and Poterba(1991) try to empirically estimate the degree of integration among national stock markets. All these studies are based on larger data set and newer methodologies, they find high and statistically significant level of interdependence between markets supporting the assumption that global stock markets are becoming more integrated. This may led to think that greater global integration implies lesser benefits from international portfolio diversification.

Some recent studies have concentrated on estimating cross country correlations and covariances. For instance, Karolyi and Stulz (1996) explore the fundamental factors that affect cross-country stock return correlations. They investigate daily returns comovements for the US and Japanese stock markets deriving an expression for asset returns covariances in order to identify their determinants. They distinguish between *global* and *competitive* shocks for asset returns, the first are associated with high return covariances while the latter with low covariances. Using high frequency data they find evidence that US and Japanese cross country return covariance exhibits a number of predictable patterns.

Using monthly stock returns data, Ammer and Mei (1994) find that most of the covariance between national indices is explained by comovements across countries in common stock risk premia rather then by comovements in fundamental variables. Longin and Solnik (1995) find that correlations increase over time, are larger when big shocks occur and are related to dividend yields and interest rates.

A short review of this literature seems to show that an increasing level of integration among markets would cause market to move together so portfolio diversification in this context would be ineffective. Even so scholars and practitioners still show a large interest in international diversification and, what is more interesting, is that an increasing number of financial companies keep on investing a large amount of money in international markets. A possible answer to this could be found in Malliaris and Urrutia (1996), who assume that certain global events tend to move world equity markets in the same directions. They find that almost all stock markets fell together during the October 1987 crash and the Iraqi invasion in Kuwait in 1990 despite the existing differences among various national economies. In the absence of these global events national markets are dominated by domestic fundamentals. Similar findings are reported by Marsh and Pfleiderer (1997) and Brooks and Del Negro (2002) who find that country-specific shocks are the predominant source of variation in returns for the average stock and the global stock market portfolio.

From this short review of the literature it is apparent that most of the empirical studies rely on traditional methodologies and investigating the existence of common trends and cycles in international stock markets may provide a deeper understanding of the stock market dynamic and their interrelationship.

3 Methodology

Stock and Watson (1988) demonstrate that if a set of n variables are cointegrated with r cointegrating vectors, these series share $n-r$ common trends. Engle and Kozicki (1993) have introduced the general concept of common features, which are data features that are present in individual series but absent from some linear combinations of those series. They develop a test for the cofeature rank which is analogous to the Johansen(1988) test for the number of cointegrating vectors. If the cofeature rank is s then this implies $n-s$ common cycles. Vahid and Engle (1993) use the framework of Beveridge-Nelson-Stock-Watson (BNSW) (1981) decomposition to identify common trends and cycles. They develop a test for common cycles and a procedure to estimate the number of common cycles given the existence of common trends. When a common serial correlation feature among the first differences of a set of cointegrated I(1) variables may be identified, common trends and common cycles from their levels can be determined. When the number of cointegrating vectors plus the number of common serial correlation features is equal to the number of variables then this framework allows a very easy recovery of trend and cycle components.

Trend-cycle decomposition is motivated by the idea that the log of the stock prices could be thought as the sum of a component that accounts for long term behavior and a stationary[1] transitory deviation from the trend. In our analysis we use the trend-cycle decomposition of an n-vector, y_t, of $I(1)$ variables

$$y_t = \tau_t + \psi_t \qquad t = 1, \ldots, T \tag{1}$$

$$\tau_t = \tau_{t-1} + \mu + \eta_t \qquad \eta_t \sim i.i.d.N\left(0, \sigma_\eta^2\right) \tag{2}$$

where $\{y_t\}$ is the observed series, $\{\tau_t\}$ is the unobserved permanent component represented by a random walk with mean growth rate, μ, and $\{\psi_t\}$ is the unobserved, stationary and ergodic transitory component, the *cycle*.

[1] The stationary component is usually referred to as the *cycle* component

This representation of a series as the sum of a trend and a cycle has some intuitive application and has a long history in statistical modeling, (see Engle and Granger (1987) Engle and Yoo (1991), Fuller (1991)).

There is no unique way to realize decomposition [1] and several different methods could be used based on different assumptions, i.e. the unobserved component approach, (see Harvey (1985) and Clark (1987)), or the Beveridge and Nelson approach, which produces models with different properties. In this paper we consider the approach adopted by Vahid and Engle (1993) based on a multivariate generalization of the Beveridge-Nelson decomposition.

3.1 The Vahid-Engle framework

Stock and Watson (1988) provide a multivariate generalization of the Beveridge-Nelson (1981) decomposition of an ARIMA model into a trend and a cycle components, where the innovations in the two components are perfectly correlated. Given a n vector of I(1) variables $\{y_t\}$ whose first difference $\{\Delta y_t\}$ is autoregressive and therefore $I(0)$, according to the classical infinite order linear moving average Wold representation, any time series can be written in a way that summarizes the unconditional variance and autocovariances of the series :

$$\Delta y_t = \tilde{\mu} + A(L)\, e_t = A(1)\, e_t + (1-L)\, A(L)\, e_t \tag{3}$$

where $A(L)$ is a matrix polynomial in the lag operator, e_t is the error term and L, the long run effect of shocks, $A(1)\, e_t$, has been separated from the rest.

Integrating up this equation defines the multivariate version of the Beveridge-Nelson (1981) decomposition

$$y_t = A(1) \sum_{i=0}^{\infty} e_{t-i} + A(L)\, e_t \tag{4}$$

where the first term is the trend component (a random walk), that is the value the series would take if it were on its long run path, and the second term is the "cycle" or stationary component.

3.2 Cointegration and Cofeatures

If there is cointegration in (4) the long run impact matrix $A(1)$ is:

$$A(1) = I + \sum_{i=1}^{p} A_i \tag{5}$$

and

$$A_i^* = \sum_{i>1}^{p-1} A_{i+1}, \qquad i = 0, ..., p-2 \tag{6}$$

$$A_{p-1}^* = A_p^* = 0 \tag{7}$$

where p is the lag order. If $A(1)$ is of reduced rank $k = n-r$ it can be written as the product of two $n \times k$ matrices of full column rank k, α and β, $A(1) = \alpha\beta'$ and the trend part can be reduced to linear combinations of k random walks rather than n. β is the matrix containing the linearly independent rows of $A(1)$ which are known as the cointegrating vectors and are stationary. The element of α are the corresponding adjustment coefficients.

In equation (3) cointegration implies that $\beta' A(1) = 0$ and that the cointegrating combinations will be linear combinations of the cyclical part of y_t. $\beta' y_t = \beta' A^*(L)$, then the first term in (4) becomes:

$$A(1) \sum_{i=0}^{\infty} e_{t-i} = \alpha\beta' \sum_{i=0}^{\infty} e_{t-i} = \alpha\tau_t \tag{8}$$

where τ_t is a vector of common trends defined by (2).

If we define $\tau_t = \beta' \sum_{i=0}^{\infty} e_{t-i}$ and $\psi_t = A^*(L) e_t$, we have the Stock and Watson (88) common trend representation defined in (1). As Wickens (1996) shows β is not uniquely defined so that these trends are not uniquely defined without introducing additional identifying conditions.

Engle and Kozicki (1993) introduce the concept of common features, which are data features that are present in individual series but absent from a linear combination of those series. In particular Vahid and Engle (1993) looked at the feature of common serial correlation, called serial correlation common feature (SCCF hereafter), among variables which, if it exists, implies common cycles. "*Elements of Δy_t have a serial correlation common feature if there exists a linear combination of them which is an innovation with respect to all observed information prior to time t. Such linear combination is called a cofeature combination and the vector which represents it is called a cofeature vector*". In other words, SCCF exists if the serial correlation in Δy_t is such that a linear combination of Δy_t exists which do not exhibit autocorrelation. They use a test developed by Engle and Kozicki to test the cofeature rank. This test is based on canonical correlation analysis along the lines of the Johansen (1988) test for the number of cointegrating vectors. If the serial correlations cofeature rank is s, then this implies $n - s$ common cycles.

Vahid and Engle also show that a SCCF among the first difference of cointegrated $I(1)$ variables implies that the remainders, after removing their common trends from their level, are also in common.

In the same way that common trends appear in (4) when $A(1)$ is of reduced rank, common cycles appear if $A^*(L)$ is of reduced rank. The presence of common cycles requires that there are linear combinations of the elements of y_t that do not contain these cyclical components, i.e. that there are sets of s linearly independent vectors gathered together in the $n \times s$ matrix ,Φ, such that

$$\Phi' c_t = \Phi' A^*(L) e_t = 0 \tag{9}$$

According to Engle and Vahid if there exist s linearly independent combinations of the elements of a set of n $I(1)$ variables which are random walks than those variables must share $(n - s)$ common cycles.

The set of cofeature vectors $\widetilde{\beta}$ must be linearly independent of the cointegration vectors β and it has to be the case that $r + s \leq n$. If $r + s < n$ then the trend and the cycle decomposition in the Vahid and Engle framework is not unique. However, in the special case that $r + s = n$, the matrix

$$C = \begin{bmatrix} \widetilde{\beta}' \\ \beta' \end{bmatrix} \tag{10}$$

is squared and of full rank with a conformably partitioned inverse defined by

$$C^{-1} = \begin{bmatrix} \widetilde{\beta}^- & \beta^- \end{bmatrix} \tag{11}$$

and it follows that we obtain the unique trend cycle decomposition described by (1)

$$y_t = C^{-1} C y_t = \widetilde{\beta}^- \widetilde{\beta}' y_t + \widetilde{\beta}^- \widetilde{\beta}' y_t = P \psi_t + (I_n - P) \Phi c_t \tag{12}$$

where $P = \widetilde{\beta}^- \widetilde{\beta}'$ is an idempotent projection matrix and $\beta^- \beta' = I - P$.

The test for common cycles is a test for a serial correlation common feature in differences developed by Vahid and Engle (1993). The test is based on the two stage least square regression of one of the variables on other using the lagged values of all variables as instruments and testing the overidentifying restrictions implied by this pseudo-structure. Intuitively this procedure is investigating if the dependence of one of the variables with the past is only through the channels that relate other variables to the past. The test statistic for the null hypothesis that the dimension of the cofeature space is at least s (or equivalently that there are at least $n - s$, common cycles) is:

$$C(p,s) = -(T-P-1)\sum_{i=1}^{s}\log\left(1-\lambda_i^2\right) \qquad (13)$$

where $\lambda_i^{2\prime}s\,(i=1,....,s)$ are the s smallest canonical correlation between the series. Under the null, this statistics has a χ^2 distribution with $\chi^2_{s^2+nsp+sr-ns}$ where n is the dimension of the system, p, is the lag order of the system in differences (which is one less than the autoregressive order in levels) and r is the number of cointegrating order in the system.

4 Empirical results

The methodology described in the previous section is applied to model international stock markets dynamics. We analyze US, UK, Japan and Canada stock markets using monthly indexes collected for the period 1978- 2002.

4.1 Time series properties of the data

The data are plotted in natural logarithms as shown in Figure 1. It is interesting to notice how the dynamics of the stock index in the three countries, U.K., the U.S. and Canada, show comparable features while the Japan stock index seems to follow its own dynamic.

Figure 1

The order of integration of the series is tested using the Augmented Dickey-Fuller (ADF) test. Suppose that data are generated from an AR(p) process, $y_t = \alpha + \sum_{i=1}^{p}\phi_i y_{t-i} + \eta_t$;we can rewrite the process in an error correction form:

$$\Delta y_t = \alpha + c y_{t-1} + \sum_{i=1}^{p-1}\phi_{t-i}\Delta y_{t-i} + \eta_t$$

where $\Delta y_t = y_t - y_{t-1}$, $c = -1 + \sum_{i=1}^{p}\phi_i$, and $\phi_i = -\left(\phi_{i+1} + ... + \phi_p\right)$ for $i = 1, \ldots, p-1$. The error correction form is convenient since only one term the, y_{t-1}, is the integrated process of order one, $I(1)$, under the unit root hypothesis, while the rest of the terms are stationary. The regression "t-ratio" of the estimator of c to its standard error from OLS regression of $I(1)$ is used to test the null hypothesis of a unit root with the critical values. Relatively high *p-values* suggest that we cannot reject the null hypothesis of a unit root in each series; however we reject the null hypothesis in their first differenced series (table 1).The number of used lags[2] are also reported.

[2]Lags for ADF test are obtained by AIC and Schwarz information criteria.

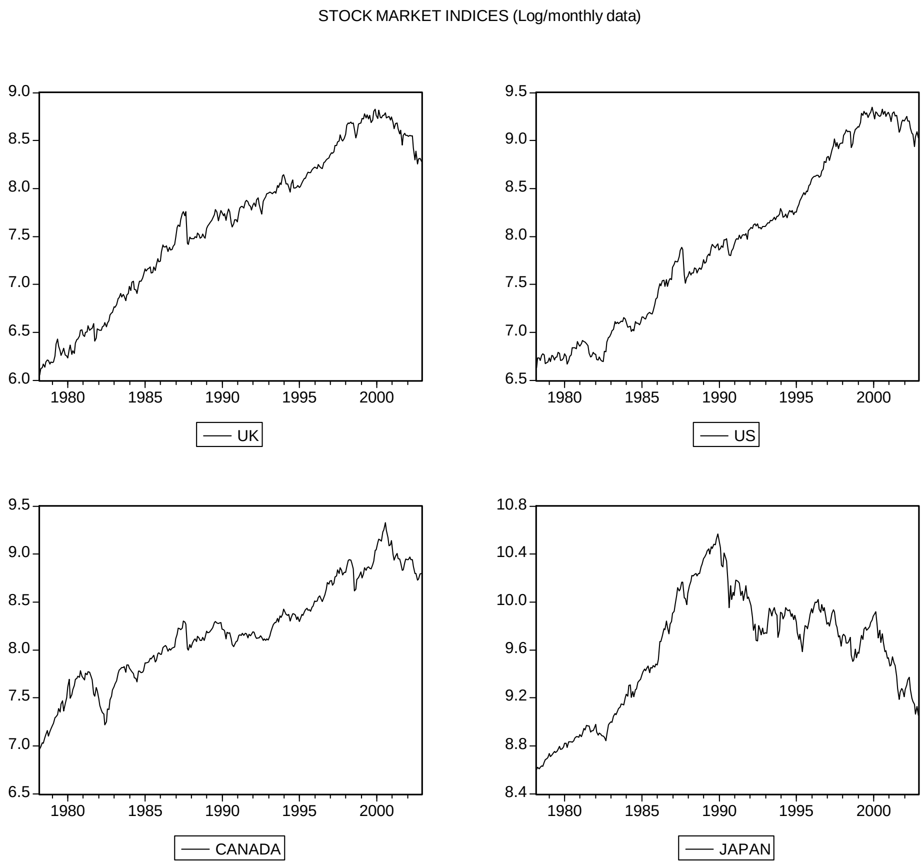


Figure 1: *Stock markets indices*

Table1. Augmented Dickey Fuller Tests

Variable	Levels	lag length	p-values
US	-2.2596	1	0.4543
UK	-1.1625	2	0.9153
J	-0.4183	1	0.9865
C	-3.0506	1	0.1206

We then examine the number of cointegrating vectors between four variables based on the maximal eigenvalue and trace statistic tests. We consider a 4-dimensional VAR(p) model for $A_t = (US_t, UK_t, J_t, Ct)$:

$$A_t = \delta + \sum_{i=1}^{p} \phi_i A_{t-i} + \varepsilon_t \tag{14}$$

where δ is a 4×1 vector of constant terms, Φ is a 4×4 matrix of parameters, and ε_t is white noise with positive definite covariance matrix $\sum \varepsilon$.If $A_t = (US_t, UK_t, J_t, Ct)$ are cointegrated, (14) has the error correction representation form:

$$\Delta A_t = \delta + \Phi A_{t-1} + \sum_{i=1}^{p-1} \Phi_i^* \Delta A_{t-i} + \varepsilon_t$$

where $\Phi = -I_4 + \sum_{i=1}^{p} \Phi_i$ has a rank of one, $\Phi_i^* = -\sum_{k>i}^{p} \Phi_k$and I_4 is a 4×4 identity matrix.

We use the Johansen's (1988) maximum likelihood methodology which is based on canonical correlation analysis. The likelihood ratio test for the hypothesis, that there are at most r cointegration vectors, is:

$$-2 \ln Q = -T \sum_{i=r+1}^{p} \log \left(1 - \hat{\lambda}_i\right) \tag{15}$$

where $\hat{\lambda}_{r+1}, ..., \hat{\lambda}_p$ are the $p - r$ smallest canonical correlations.

We estimate a VAR (2)[3] model with unrestricted constant and no trend in the cointegration space. The results of the Johansen's analysis are reported in table 2. They indicate the existence of one cointegrating vector $r = 1$, as it is shown by the trace test at the 5% significative level. This implies, following Vahid& Engle () , that there are $3 = 4 - 1$ common stochastic trends.

[3] Akaike information Criterion and LR test suggest to use up to 2 lags.

Table 2. Johansen test for cointegrating vector

H_0	λ	$\lambda_{\max}$	$\lambda_{\max}^{5\%}$	λ_{trace}	$\lambda_{trace}^{5\%}$
$r = 0$	0.085	26.37	27.07	52.71	47.21
$r \leq 1$	0.052	15.94	20.97	26.35	26.98
$r \leq 2$	0.029	8.61	14.07	10.40	15.41
$r \leq 3$	0.006	1.76	3.76	1.80	2.71

The estimated cointegration relation with normalization is

$$Z = \ln(US) - 0.994832 \ln(UK) + 0.203982 \ln(J) - 0.317568 \ln(C) \quad (16)$$

4.2 Trend and cycle decomposition

When the rank of Φ is one,$\Phi = \alpha \cdot \beta$, where α is a non-zero parameter matrix of speed of adjustment and β is a normalized 1×4 row vector of long-run equilibrium such that $\beta' \cdot A_{t-1}$ is stationary. Therefore, the rank of the coefficient matrix Φ is examined for the long-run equilibrium information. We need to determine the rank of the coefficient matrix Φ as well as the AR order p of the model (14). The AR order p of A_t in model (14) is identified by partial canonical correlation analysis PCCA between A_t and A_{t-1}. .

Given that the 4 stock markets are cointegrated we test for the number of cofeature vectors in these indices. The possibility of common cycles is then investigated using the cofeature test described in Vahid and Engle (1993). This is based on the canonical correlations of the first differences of the data with their lags (1) and the error correction term lagged once. The squared canonical correlations and the value of the test statistic for the number of cofeature vectors are reported in table 3.

Table 3. Cofeature Analysis: Vahid and Engle tests

H_0	λ_i^2	C(p,s)	DF	$p-value$
$s > 0$	0.005	1.464	2	0.513
$s > 1$	0.011	3.394	6	0.479
$s > 2$	0.027	13.081	12	0.373
$s > 3$	0.156	63.283	20	0.000

At 5% significance level, the test indicated the existence of $s = 3$ cofeature vectors, implying $r = n - s = 1$, common cycle. This satisfies the restriction $r + s = n$ that allows the simple Vahid and Engle decomposition. The cofeatures vectors which are the canonical variates corresponding to the three smallest canonical correlations after normalizations are:

$$\begin{aligned} \Delta LNIK &= 2.194\Delta LDOW \\ \Delta LSPTSX &= 3.239\Delta LDOW \\ \Delta LFTSE &= 4.069\Delta LDOW \end{aligned} \tag{17}$$

Following Vahid and Engle, we estimate the pseudo-structural system and obtain standard errors for the estimates of the structural parameters. We use the information that one unforecastable combination exists, so we can add one unrestricted reduced form equation for $\Delta LDOW$ to the equations reported in (17) and estimate the four equations jointly using a system estimation method. We use the FIML procedure and obtain the following estimates and the standard errors (in parenthesis):

$$\begin{aligned} \Delta LNIK &= \underset{(0.11)}{2.187}\Delta LDOW + \underset{(0.0003)}{0.014} \\ \Delta LSPTSX &= \underset{(0.44)}{3.132}\Delta LDOW + \underset{(0.002)}{0.02} \\ \Delta LFTSE &= \underset{(0.32)}{3.069}\Delta LDOW + \underset{(0.005)}{0.01} \end{aligned}$$

This means that the four countries share one independent serially correlated cycles. In other words, we observed the same cyclical behaviors for the four countries.

4.3 Sectorial trends and Cycles

This section describes the set of sectorial trends and cycles resulting from the model described above imposing the restriction of three common trends and one common cycle. The trend is a random walk with drift. Figure 2 plots the common cycle for the four markets and Figure 3 shows the cyclical component for each of the log indices. The cyclical pattern is comparable for UK, and Canada and it is positive from 78 to 84 and then shows an alternating behavior. The cyclical component for US and Japan is very similar and it shows an inverted behavior respect to the other two. As a cyclical component is derived from the actual series deviating from the trend and given that the cyclical components for the four markets is not always positive or negative we cannot say in general that the stock market performances in each market achieve high market levels than their long term trends do. For UK and Canada the higher performance could be recognized only over the period 78-84 after that the performance seems to be more or less in line with the trend; for the Japanese and US stock markets the cyclical pattern seem to be much closer to the trend component for the entire period. The inverse relationship between the cyclical component of US and Japan respect to the UK and Canada emphasizes the significance of the US and Japanese markets as the leading countries for investments in the western countries.

Figure 2

Figure 3

In figures 4–7 the trend and cycle decomposition for each country is provided. Their features are reported in order to better understand the nature of each stock market. The four markets can be classified as trend-dominated markets due to their below zero cyclical components. The trends in the four countries are quite comparable and they seem to follow similar patterns and directions toward the future regardless the condition of the markets. The fact that the analyzed markets show a dominant trend component over the entire period could be explained by the fact that the economic fundamentals for each country dominate financial market dynamics. Some exception may be identified by Japan where the series itself is variable and the estimated trend is therefore much more variable.

5 Conclusion

In this paper we address the issue of increasing global integration of international stock markets. Using a Vector Error Correction Model we identify a long run component and a cyclical component in the four-vector composed of stock market international indices. Using data for the period 1978-2002 we succeed in decomposing the time series, in a Beveridge-Nelson-Stock and Watson framework, in 3 common trends component and one common cycle.

This findings could be helpful trying to analyze the recent benefits deriving from international portfolio diversification. This supports the idea that there is a long run component in the international markets dynamics which is dominated by a trend behavior and a short run component, represented by a common cyclical behavioral of the four markets. This intuitively may lead to think that in the short run market move together especially in response to certain global events (i.e. '87 crash, '91 Iraqi invasion and September 11 2001), while in the long run they are trend dominated and therefore their dynamic is driven by domestic fundamentals.

When we assume that a common cycles component could be identified among the four major international stock markets -US, Japan, UK and Canada- most of the international diversification benefits may be eliminated.

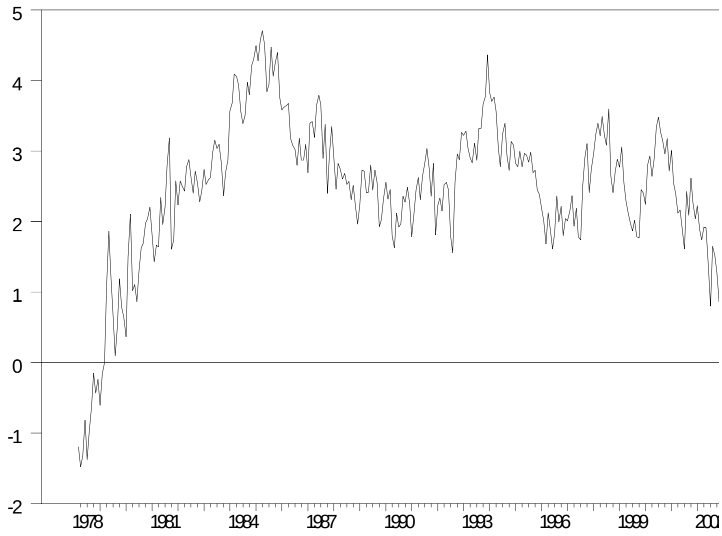


Figure 2: *Common Cycle for the four series*

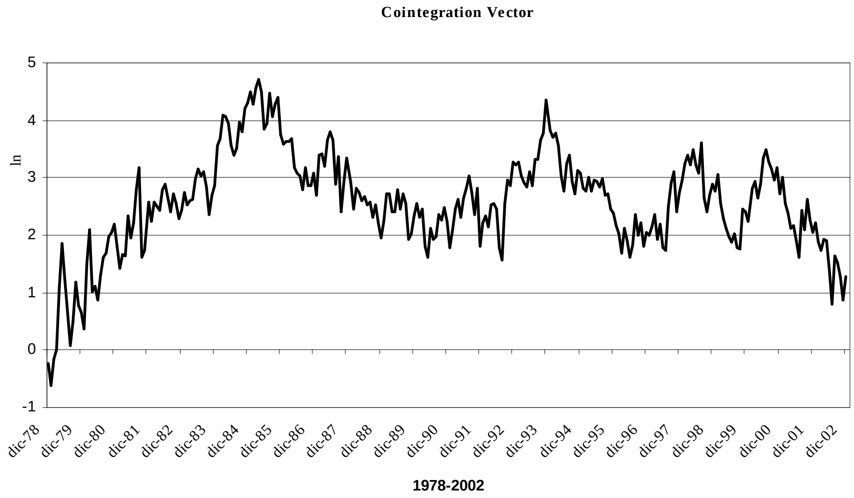


Figure 3: Common Cycle for the four countries

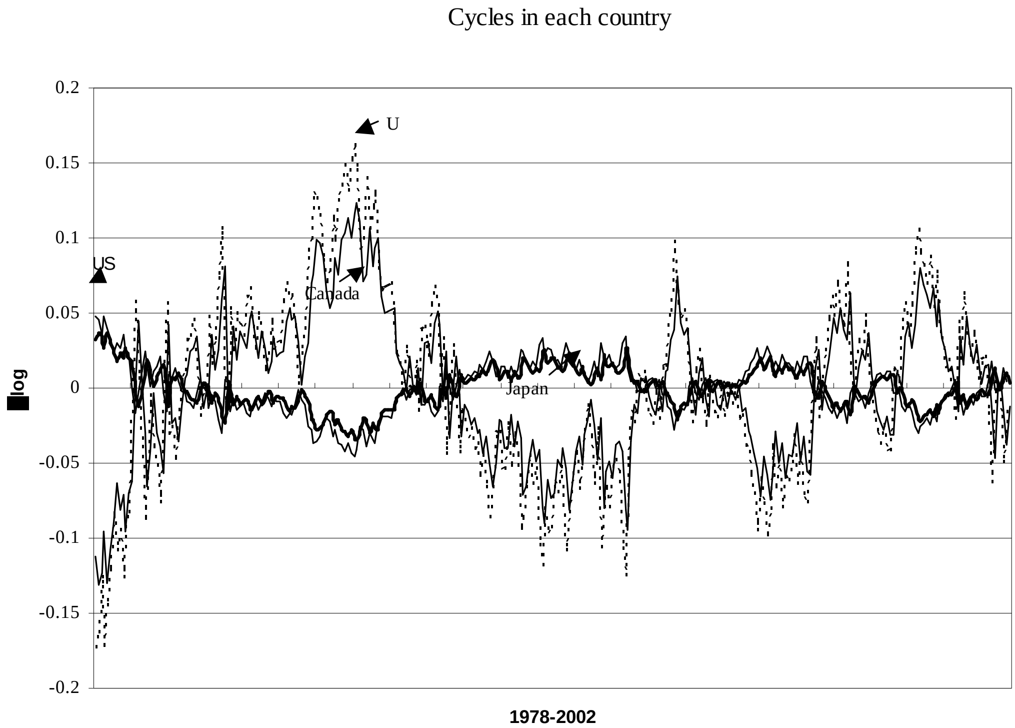
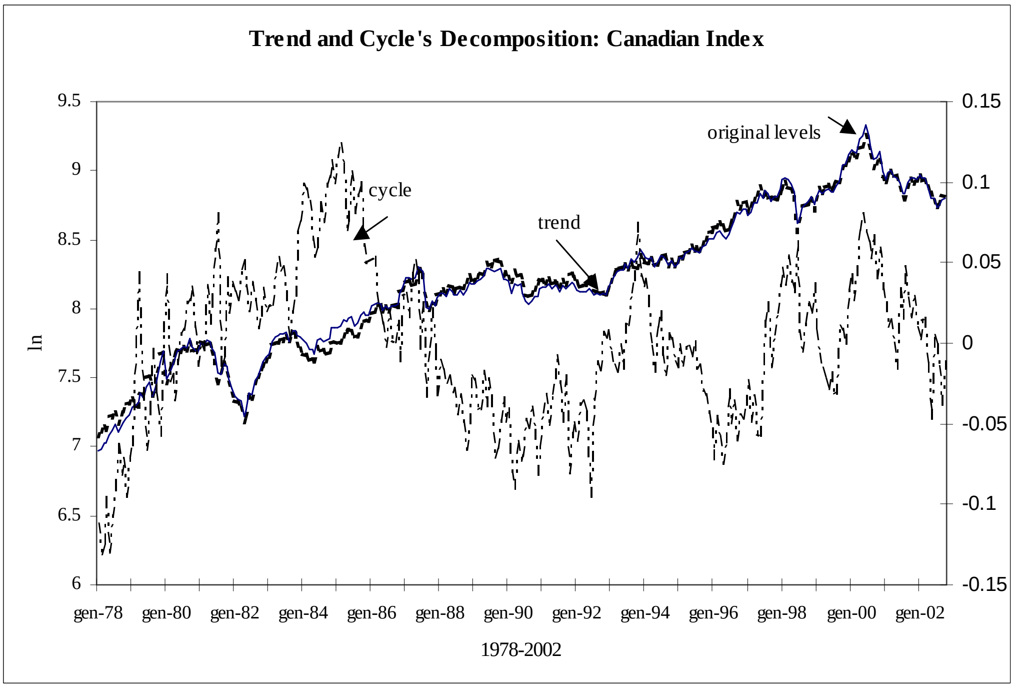


Figure 4: Cycle component for each country


Trend and Cycle's Decomposition: Canadian Index
ln
original levels
cycle
trend
9.5
9
8.5
8
7.5
7
6.5
6
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
gen-78
gen-80
gen-82
gen-84
gen-86
gen-88
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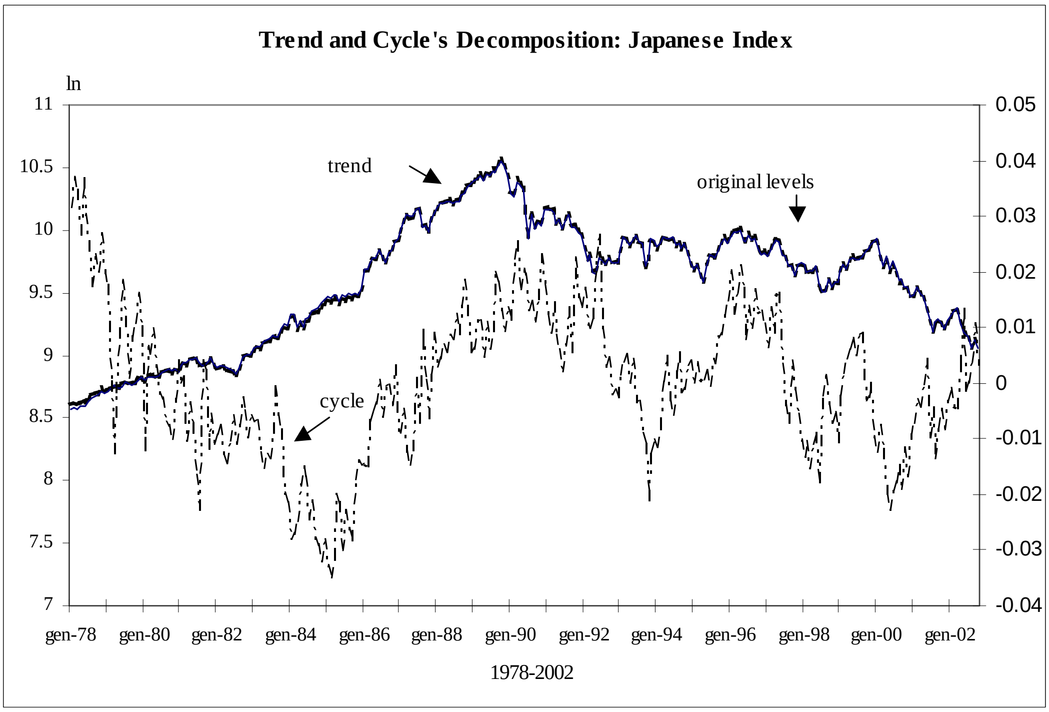
gen-98
gen-00
gen-02
1978-2002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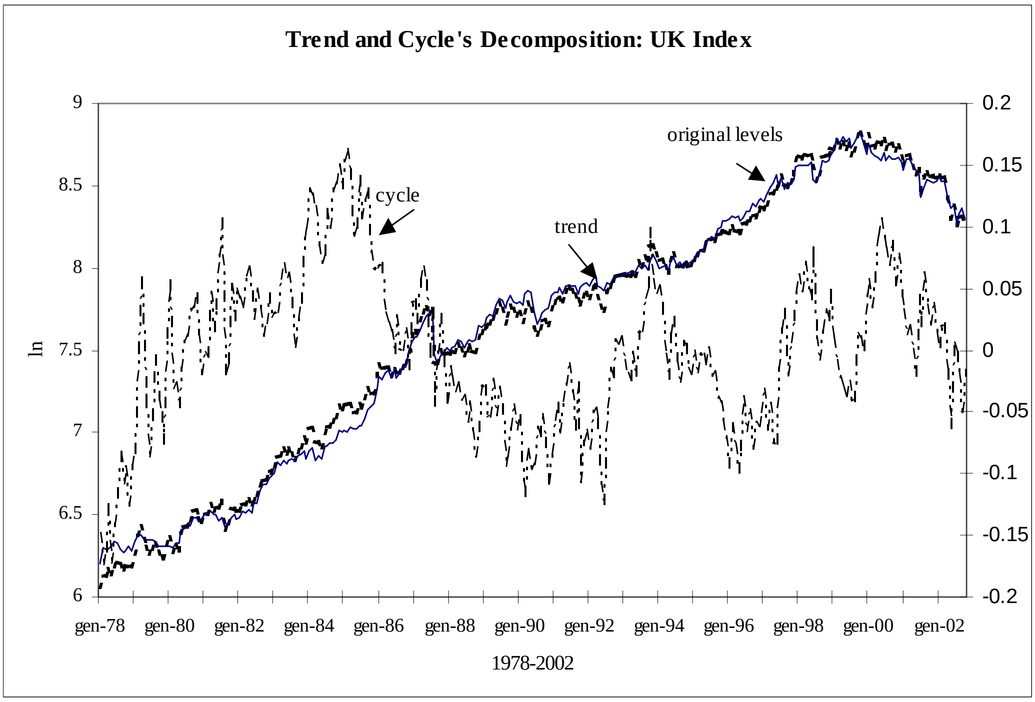
ln
trend
original levels
cycle
11
10.5
10
9.5
9
8.5
8
7.5
7
0.05
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
gen-78
gen-80
gen-82
gen-84
gen-86
gen-88
gen-90
gen-92
gen-94
gen-96
gen-98
gen-00
gen-02
1978-2002



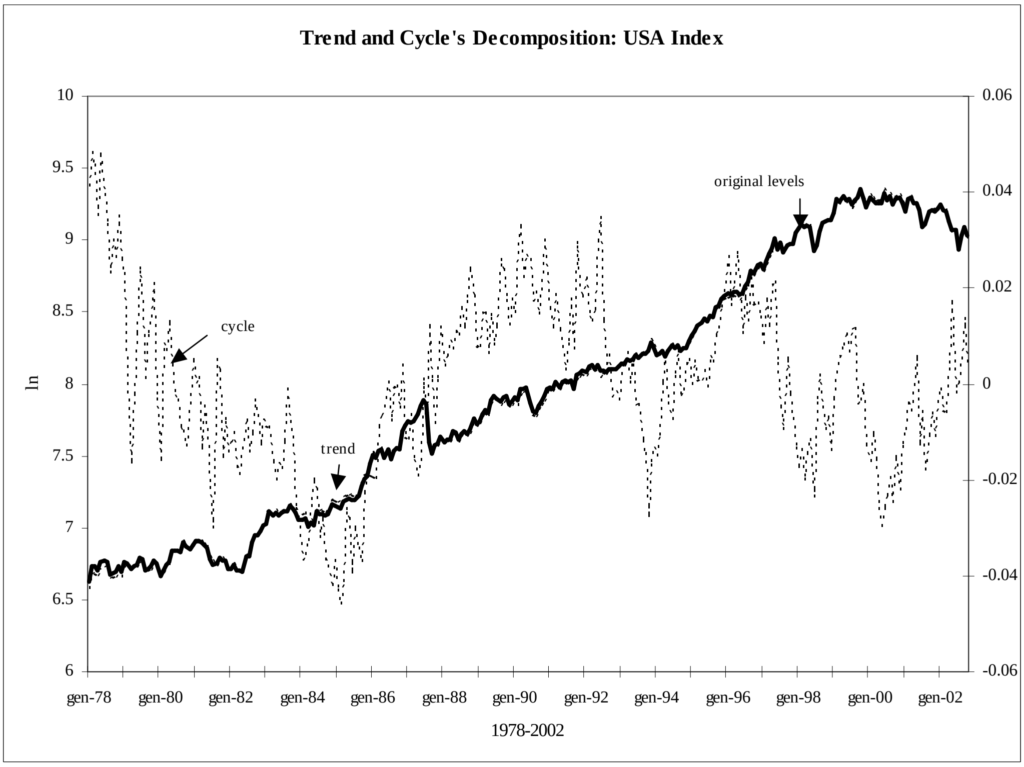
This could be explained supporting the assumptions made by McCarthy and Najand who find that US market exerts most influence on other markets and so the US stock market could be addressed as the leader stock markets which determine the short run dynamics of the international financial markets. On the other hand, in the long run three different trends could be identified and this may support the assumption that diversification may pay in a long run horizon since stock markets behavior are dominated by economic domestic fundamentals.

6 Appendix

The portmanteau and adjusted portmanteau tests compute multivariate Box-Pierce/Ljung-Box Q-statistics for residual serial correlation up to the specified order. The test checks the null hypothesis:

$$H_0 : E\left(u_t u_{t-i}\right) = 0, \qquad i = 1, ..., h > p$$

against the alternative that at least one autocovariance and, hence, one autocorrelation is non zero. The test statistics takes the form (Lütkepohl,1991;


Trend and Cycle's Decomposition: USA Index
10
9.5
9
8.5
8
7.5
7
6.5
6
ln
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
original levels
cycle
trend
gen-78
gen-80
gen-82
gen-84
gen-86
gen-88
gen-90
gen-92
gen-94
gen-96
gen-98
gen-00
gen-02
1978-2002

Lütkepohl and Krätzing, 2004):

$$Q_h = T\sum_{i=1}^{h} tr\left(\widehat{C}_i^{'}\widehat{C}_0^{-1}\widehat{C}_i^{'}\widehat{C}_0^{-1}\right) = Tvec\left(\widehat{C}_h\right)^{'}\left(I_h \otimes \widehat{C}_0^{-1} \otimes \widehat{C}_0^{-1}\right) vec\left(\widehat{C}_h\right)$$

where $\widehat{C}_i = T^{-1}\sum_{t=i+1}^{T}\widehat{u}_t u_{t-i}^{'}$ and $\widehat{u}_t$'s. are the residual from a stable VAR(p) process. Under the null hypothesis Q_h has an approximate $\chi^2\left(K^2\left(h-p\right)\right)$ .Liung and Box(1978) find that in the small samples the nominal size of the portmanteau test tend to be lower than the significance level chosen. Therefore, a modified portmanteau test has been provided:

$$Q_h^* = T^2\sum_{i=1}^{h}\left(T-i\right)^{-1} tr\left(\widehat{C}_i^{'}\widehat{C}_0^{-1}\widehat{C}_i^{'}\widehat{C}_0^{-1}\right)$$

Table 4. VAR Residual Portmanteau Tests for Autocorrelations

Lags	Q-Statistics	Prob.	Adj Q-Statistics	Prob.	df
1	0.648695	NA*	0.650894	NA*	NA*
2	20.83358	NA*	20.97309	NA*	NA*
3	37.87809	0.0216	38.19212	0.0104	16
4	47.53400	0.0579	47.98030	0.0534	32
5	63.27797	0.0687	63.99478	0.0610	48
6	76.21456	0.1410	77.19903	0.1245	64
7	91.60996	0.1764	92.96733	0.1523	80
8	111.5841	0.1321	113.4963	0.1074	96
9	111.5841	0.3064	121.1982	0.2602	112
10	145.8999	0.133	148.9851	0.0990	128
11	156.0453	0.2327	159.5220	0.1781	144
12	177.7014	0.1606	182.0933	0.1114	160

*The test is valid only for lags larger than the VAR lag order

LM test for residual serial correlation is provided by the following statistics:

$$LM(s) = \left(T - pk - m - p - \frac{1}{2}\right)\log\frac{\left|\widehat{\Omega}\right|}{\left|\widetilde{\Omega}\right|}$$

and is asymptotically distributed as χ^2 with degrees of freedom given by $f = p^2$. The test statistic is calculated by regressing the estimated residual from a p-dimensional autoregressive process with i.i.N(0, Ω) errors ϵ_t

$$Y_t = \Pi_1 Y_{t-1} + ... + \Pi_k Y_{t-k} + \Phi D_t + \epsilon_t, \quad t = 1, ...T$$

on the residual lagged as well as in above model (Johansen 1995).

Table 5. VAR residual Serial correlation LM tests

Lags	LM-Statistics	Prob
1	18.44228	0.2986
2	23.00830	0.1135
3	18.07762	0.3194
4	9.977246	0.8678
5	16.48720	0.4195
6	13.53642	0.6332
7	16.06179	0.4487
8	21.10039	0.1747
9	7.976665	0.9497
10	28.73525	0.0258
11	10.75914	0.8241
12	22.38803	0.1311

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